HYPERSPECTRAL IMAGING: CALIBRATION AND APPLICATIONS WITH NATURAL SCENES

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ABSTRACT

Hyperspectral imaging is a technique which combines spectral and spatial imaging methods. The technology is used in remote sensing, medicine, agriculture and forensics just to mention a few. Non-remote systems are developed by using sensor designs different from push-broom and whisk- broom methods, commonly found in remote sensing hyperspectral imaging systems. Images are commonly acquired by mounting various electronically tunable filters in front of monochromatic cameras and capturing a range of wavelengths to produce a spectral image cube. Illumination plays a major role during imaging, as both the camera and electronically tunable filter may suffer low transmission at the ends of the visible spectrum, resulting in a low signal to noise ratio.

The work described in this thesis attempts to address two key objectives. The first was to identify the main sources of errors in a common design of focal-plane hyperspectral imaging system and devise ways of compensating for these errors. Calibration and characterization of a focal-plane hyperspectral imaging system included system noise characterization, stray-light compensation, flat field correction, image registration, input-output function characterization and calibration verification.

The other was to apply imaging techniques to hyperspectral images. This included scene recognition using ratio indexing and spectral gradients. This comes from the underlying idea that due to the large number of bands contained in hyperspectral images, more information is available so better recognition results compared to RGB images. A novel approach for obtaining ratios for ratio indexing is proposed in this thesis.

The imaging of archived materials from University of Manchester's John Rylands Library was also done. The aim was to produce high resolution hyperspectral images that will help in identifying accurate matches for colours used in document restoration at the Library.

DECLARATION

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Signed:

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CHAPTER ONE

INTRODUCTION

Hyperspectral imaging is a technique which combines spectral and spatial imaging methods. Although the technology was developed for remote sensing it has found uses in medicine^{16, 12, 15} and agriculture^{49, 61, 21} just to mention a few. These non-remote systems are developed by using sensor designs different from push-broom and whisk-broom methods, commonly found in remote sensing hyperspectral imaging systems. Images are commonly acquired by mounting various electronically tunable filters in front of monochromatic cameras and capturing a range of wavelengths to produce a spectral image cube. The imaging system used for this thesis falls under this category. Illumination plays a major role during imaging, as both the camera and electronically tunable filter may suffer low transmission at the ends of the visible spectrum, resulting in a low signal to noise ratio.

One of the main objectives of this research was to identify the main sources of errors in a common design of focal-plane hyperspectral imaging system and devise ways of compensating for these errors. The other was to achieve scene recognition using hyperspectral data. This comes from the underlying idea that due to the large number of bands contained in hyperspectral images, more information is available;hence better recognition results.

This chapter introduces basic radiometric terms and definitions which describe the measurement of light. The elements of human vision and the evaluation of its performance, which are fundamental to understanding judgements of image quality and colour measurement will also be discussed.

Chapter two provides a literature review of colour imaging consisting of colour matching functions, tristimulus values, colour spaces, colour difference formulae, colour gamut, and metamerism (the phenomenon by which different spectra appear identical to the eye or imaging device) including different indices used to compute mismatches among metameric pairs. The measurement of light in the visible spectrum will also be discussed and basic photometric terms will be defined.

Chapter three contains a discussion of hyperspectral imaging, in which the process of data acquisition and processing, and calibration methods are explained.

Chapter four deals with calibration and characterization of a focal-plane hyperspectral imaging system. This include system noise characterization, straylight compensation, flat field correction, image registration, input-output function characterization and calibration verification.

Chapter five presents hyperspectral imaging of archived material at the University of Manchester's John Rylands Library. Image acquisition and processing is given and evaluation of image quality is also discussed.

Chapter six contains applications of scene recognition algorithms on hyperspectral images. Spectral gradient and ratio indexing are used for scene recognition of natural scene images. A novel method for computing image pixel ratios is proposed¹⁹. Scene recognition performance appears to peak with five sensor channels, after which it possibly declines with more channels.

Chapter seven includes a general discussion of the work and suggestions for further work will also be given.

1.1 Radiometry

Optical radiation can be considered as energy propagated in the form of electromagnetic waves or particles (photons), which can be reflected, captured, or dispersed using optical components such as lenses or prisms⁴³. Radiometric measurements are based on geometric optics, with exceptions where wave and quantum optics are used to account for properties such as diffraction and the interaction with matter at the microscopic level. Measurement involves a beam of radiation originating from a source, passing through an optical path and being captured by a radiometric instrument.

Some definitions and concepts will be introduced to help understand the flow of radiation through various stages of image formation. The following concepts are fundamental terms associated with optical imaging systems.

Radiance

Radiance can be evaluated on any surface through which radiant flux or power passes through. This includes surfaces of sources, receivers and any optical elements such as lenses and mirrors. Radiance is defined as the radiant flux or power per unit solid angle ω in a given direction per unit projected area dA perpendicular to a given direction⁶² (Figure 1.1). It is expressed mathematically in Equation 1.1.1

$$L(x, y, \theta, \phi) = \frac{d^2 P(x, y, \theta, \phi)}{dA \cdot \cos \theta \cdot d\omega}$$
(1.1.1)

where $L(x, y, \theta, \phi)$ is the radiance at point (x, y) in the ray direction (θ, ϕ) , $d^2P(x, y, \theta, \phi)$ is the radiant flux or power passing through the surface element dA at point (x, y) and



Figure 1.1: Radiance of a surface element

within the element of solid angle $d\omega$, and $dA \cdot \cos \theta$ is the element of projected area which is perpendicular to the ray direction (θ, ϕ) . The SI unit for radiance is watts per metre square per steradian i.e. Wm⁻²sr⁻¹.

Radiance measurement is useful because it indicates how much of the radiant power emitted by an emitting or reflecting surface will be received by an optical system looking at the surface from some angle of view.

Irradiance and radiant exitance

Radiant flux describes the amount of radiant energy that is incident on a surface or emitted from a surface. When radiant flux is irradiated on a surface it is known as irradiance. It is the amount of radiant flux per unit area, while radiant exitance is associated with radiant flux leaving a surface. Both terms have the same unit watts per metre square Wm^{-2} . In hyperspectral imaging, we consider these quantities for individual wavelength or bands of wavelengths. When this is done for radiation incident on a surface, it is called spectral irradiance, and has radiometric units Wm^{-3} .

Reflectance

Reflectance is the basic quantity that characterises the process of reflection, which is a physical process in which radiant energy incident on a material is at least partially returned by the material without change of wavelength⁶⁹. It is defined as the ratio of reflected radiant flux (or power) to incident radiant flux (or power). Its value is between 0 and 1. Spectral reflectance $\rho(\lambda)$ is defined in Equation 1.1.2 as

$$\rho(\lambda) = \frac{P_{\lambda}}{P_{0\lambda}} \tag{1.1.2}$$

where P_{λ} is the spectral concentration of radiant power reflected by a material and $P_{0\lambda}$ is the spectral concentration of radiant power incident on the material⁶⁹. Surface reflectance can be described by its bidirectional distribution function (BRDF) and is considered in the next section.

1.1.1 Bidirectional reflectance distribution function

The bidirectional reflectance distribution function (BRDF) gives a description of how light is reflected at surfaces with respect to its spatial and spectral variables. The following is based on Nicodemus et al.⁴⁴.



IRRADIATED ARÉA, A

Figure 1.2: Birdirectional reflectance distribution function

In Figure 1.2, A represents the total surface area irradiated. The irradiance from the direction (θ_i, ϕ_i) inside the solid angle $d\omega_i$ and striking an element of the surface with area dA is given by $d\Phi_i$. The reflected radiance in the direction (θ_r, ϕ_r) which originates from $d\Phi_i$ is represented as dL_r . In general, dL_r is directly proportional to $d\Phi_i$. The BRDF f_r is simply defined as the ratio of the reflected radiance in the viewing direction to the irradiance in the direction of the incident light. The incident and reflected direction angles are defined with respect to the surface normal.

$$f_r(\theta_i, \phi_i; \theta_r, \phi_r) \equiv \frac{dL_r(\theta_i, \phi_i; \theta_r, \phi_r)}{dE_i(\theta_i, \phi_i)}$$
(1.1.3)

The BDRF is modelled using the assumption there is uniform irradiance over a large area of a uniform and isotropic surface⁴⁴. The BRDF can be extended to include the wavelength or bands of wavelength of light as a variable. This function is known as the bidirectional spectral-reflectance distribution function (BSRDF). The BSRDF of a surface records the percentage of incoming light that is reflected at each wavelength.

1.2 Light sources and illuminants

Lights sources emit radiation characterised by a spectral radiant power distribution, which gives the radiant power exitance at each wavelength or over a band of wavelengths. Examples of these sources are the sun, a candle and incandescent lamps. An illuminant can be considered as a light source that has been defined by a spectral radiant power distribution curve, but may not actually exist. The Commission Internationale de l'Eclairage (CIE) has defined illuminants which are modelled from different light sources. The spectral radiant power distribution of CIE standard illuminants are given in terms of an arbitrary unit of radiant power; hence they are referred to as relative spectral radiant power distributions⁶⁹.



Figure 1.3: Relative spectral power distribution curves for CIE Standard Illuminants A and D_{65}

Examples are Illuminants A, B and C which model incandescent light, direct sunlight and average daylight respectively. Illuminant D is used to represent different phases of daylight, while illuminant E is an equal energy radiator having constant spectral power distribution inside the visible spectrum. It is used as a theoretical reference. Figure 1.3 shows the spectral power distribution curves for illuminants A and D_{65} .

1.3 The human vision system

In the human eye, when light arrives at the cornea, it is focused by the cornea and lens onto the retina producing a small inverted image on the retina. The retinal image is transformed into a neural signal by light sensitive photoreceptors present in the retina. The retina has two types of photoreceptors, namely, rods and cones. The rods are responsible for night (scotopic) vision and cones for day (photopic) vision.

The sensitivity of the eye to light is not the same for all wavelengths. The spectral sensitivity curves for scotopic and photopic vision of the human eye are shown in Figure 1.4. These curves are obtained by having observers adjust the strength of a beam of light for a particular wavelength until its brightness matches that of a reference wavelength³³. These curves are known as the spectral luminous efficiency function for scotopic $V'(\lambda)$ and photopic $V(\lambda)$ vision. An ideal observer having a relative spectral sensitivity function that is the same as the $V(\lambda)$ function is known as a CIE standard photopic photometric observer³³.



Figure 1.4: CIE spectral luminous efficiency curves for photopic $V(\lambda)$ and scotopic vision $V'(\lambda)$

Human colour vision relies on three types of cone photoreceptors which are sensitive to light over different, but overlapping regions of the visible spectrum with sensitivities highest at 420.7 nm (short wavelength), 530.3 nm (medium wavelength), 558.9 nm (long wavelength) and are known as S, M and L cones respectively⁵⁷. Figure 1.5 gives the spectral sensitivity curves for human cones as determined by Stockman et. al⁵⁷.

The optical quality of the retinal image is degraded by diffraction, monochromatic and chromatic aberration, and light scatter. Currently, optical defects of the eye are usually described in terms of its wavefront aberration under specified conditions, the overall level of aberration being expressed as the root-mean-square (RMS) wavefront error. The optical performance of the human eye can be characterized by measuring its modulation transfer function (MTF). The modulation transfer function can be measured using the double-pass method^{53, 8, 35} or interferometric method^{66, 7}. In the double-pass method, a point source



Figure 1.5: Spectral sensitivity curves for the cones of the eye⁵⁷

of light is imaged on the retina and the reflected light from the eye is captured. This image is then used to compute the MTF. With the interferometric method, conventional sinusoidal gratings and interference fringes, which are not blurred by the optics of the eye are imaged and their contrast sensitivities are determined by subjects adjusting the contrast of the gratings or fringes on a video monitor to threshold. The MTF is then estimated as the ratio of their contrast sensitivities. The contrast sensitivity measured using sinusoidal gratings describes the transfer of contrast through the whole sequence of stages of the visual system including both the optics of the neural visual system. On the other hand, measurements of contrast sensitivity using interference fringes describes the transfer of contrast through the optics of the other hand, measurements of contrast sensitivity using interference fringes describes the transfer of contrast through the neural visual system, omitting any focussing by the optics of the eye.

1.4 Aims and objectives

One of the aims of this thesis is to identify the main sources of errors in a focal-plane hyperspectral imaging system and devise ways of compensating for these errors. The problem of low signals at short wavelengths, spatial non-uniformity in the sensitivity of the imaging system and efficiency of calibration references are particularly important sources of error. In this thesis, the calibration and characterization of a focal-plane hyper-spectral imaging system was performed. Methods used included, computation of input-output and modulation transfer functions to check the linearity of the imaging system and image quality respectively. Analysis of system noise, vignetting and straylight which affect image quality was also performed. Hyperspectral image registration algorithms were

used to align images and are presented. The evaluation of image registration accuracy was done by tracking the edge midpoint location of sharp edge regions. Final calibration verification was tested on Gretag Macbeth colour checker chart hyperspectral images.

The other aim was the application of hyperspectral imaging to archived materials and natural scenes. Imaging archived materials at the University of Manchester's John Rylands Library was undertaken. Images were corrected for noise, vignetting and straylight. Image registration algorithms presented in chapter four were applied to hyperspectral images. The metric for evaluating registration accuracy was once again edge tracking. The second application was hyperspectral imaging scene recognition. One approach was using spectral gradients of hyperspectral images to achieve recognition between images captured using different light sources. The other, was scene recognition using ratio indexing. A novel approach for creating ratio images is given in this thesis. Results show that hyperspectral imaging gives better results compared to conventional colour images.

CHAPTER TWO

COLOUR IMAGING

2.1 Introduction

Sight and colour perception are among the most fascinating human senses. Colour images can be found in television, books, and newspapers just to mention a few. In order to record and process colour images, it is essential to understand the capabilities and limitations of colour imaging devices.

In this chapter, a discussion of photometry, which describes light measurement in the visible part of the electromagnetic spectrum, is considered. Basic colorimetry, the science of colour measurement and description, with emphasis on colour matching functions, tristimulus values, colour spaces, colour difference formulae, colour gamut and metamerism, including different indices used to compute mismatch among metameric pairs is also considered.

2.2 Photometry

The fundamental concept in photometry is the matching of brightness between different stimuli⁶⁹. It is the measurement of light weighted by human luminance sensitivity. It is based on the photopic spectral luminous efficiency function $V(\lambda)$. The $V(\lambda)$ function is used as a weighting function for evaluating the total amount of light in a mixture of radiation for different wavelengths⁶⁹. Photometry is based on photopic spectral luminous efficiency function $V(\lambda)$ which was standardized by the CIE in 1951. The basic quantities used in photometric measurements are as follows:

2.2.1 Luminous flux

Luminous flux is radiant flux (or power) weighted by the $V(\lambda)$ function. The unit for luminous flux (or power) is the lumen (lm) which is the luminous flux of a beam of monochromatic radiation with frequency 540 x 10¹² hertz (555 nm) and having a radiant flux of 1/683 watt³³.

2.2.2 Luminance

The luminance is defined as the luminous flux per unit solid angle and per unit projected area, in a given direction, at a point on the surface. It is expressed mathematically in Equation 2.2.1

$$L_v(x, y, \theta, \phi) = \frac{d^2 F_v(x, y, \theta, \phi)}{dA \cdot \cos \theta \cdot d\omega}$$
(2.2.1)

where $L_v(x, y, \theta, \phi)$ is the luminance at point (x, y), dA. $\cos \theta$ is the element of projected area onto a plane perpendicular to direction θ , ϕ and $d^2F_v(x, y, \theta, \phi)$ is the luminance flux passing through the surface element dA at point (x, y) and within the element of solid angle $d\omega$. The unit for luminance is given as candela per square metre cd/m².

2.2.3 Illuminance and luminous exitance

Illuminance is the luminous flux incident on a surface, per unit area while luminous exitance is the luminous flux per unit area emitted from a surface. Both terms have the same unit which is lux.

2.3 Colorimetry

Colorimetry is the branch of colour science concerned primarily with specifying numerically the colour of a physically defined visual stimulus such that⁶⁹:

(1) Stimuli with the same specifications look alike when viewed by an observer with normal colour vision under the same observing conditions (complete colour match).

(2) The numbers comprising the specifications are continuous functions of the physical parameters defining the spectral radiant power distribution of the stimulus.

Colorimetery is also concerned with the colour difference perceived by observers when small differences in the spectral radiant power distribution of visual stimuli are such that a complete colour-match cannot be observed⁶⁹. The Commission Internationale de l'Eclairage (CIE) was the driving force behind the development of colorimetry by defining and specifying colorimetry through their publications. The fundamental theory of colorimetry involves how the so-called tristmulus values are specified. CIE tristmulus values are considered in a later section.

2.3.1 Colour-matching functions

Normal colour vision is basically a function of three variables. The three cone sensitivity curves of the human eye might seem a good basis for specifying the colour for visual stimuli. However, this was not used in establishing an internationally accepted method for evaluating colour because these curves were not known then with sufficient precision³³. Instead, three- colour matching or trichromatic matching functions are used. These functions were derived from independent experiments by W.D. Wright in 1929 and J. Guild in 1931.

The experimental procedure consisted of observers matching a test colour seen on one half of the field of view against an additive mixture of beams of red, green and blue light by adjusting the amounts of red, green and blue light until the additive mixture of colours matches the test colour. Wright used a trichromatic colorimeter with monochromatic bands of light isolated from a spectrum formed by a prism⁶⁸. He used a total of ten observers with an instrumental field size of 2°. On the other hand, Guild used a tungsten lamp with colour filters and seven observers with a field size of 2°³⁰. Guild's colour matching functions $\bar{r}(\lambda)$, $\bar{g}(\lambda)$, $\bar{b}(\lambda)$ contain negative values. In 1931, the CIE transformed the two sets of colour matching functions obtained from the experiments by Wright and Guild into a single set of colour-matching functions $\hat{x}(\lambda)$, $\bar{y}(\lambda)$, $\bar{z}(\lambda)$ having non-negative values and with $\bar{y}(\lambda)$ approximately equal to the daylight luminance sensitivity of the human eye. A plot of these functions is given in Figure 2.1.



Figure 2.1: CIE 1931 2° colour- matching functions

In 1964, a second set of colour matching functions was measured using a larger instrumental field size (10°) . One reason for this is the non-uniform distribution of cones in the retina⁶⁴. Another reason was to do with intrusion of macular pigment in the foveal 2° measurements; in the 10° matching, observers were instructed to ignore the central 2° . Both sets of colour-matching functions are used in the colour industry and users decide according to their particular viewing conditions.

2.3.2 CIE Tristimulus values

Tristimulus values are the basis of colorimetry and their accurate computation is desirable by the colour industry for a wide range of applications. A colour arising from reflected light can be specified by a triplet of tristimulus values. Estimating the tristmulus values requires the relative spectral radiant power distribution of an illuminant, reflectance function spectra and colour-matching functions. Mathematically, it is the integration of these three spectra given in Equations 2.3.1, 2.3.2 and 2.3.3.

$$X = \int_{\lambda} \bar{x}(\lambda) E(\lambda) R(\lambda) d(\lambda)$$
(2.3.1)

$$Y = \int_{\lambda} \bar{y}(\lambda) E(\lambda) R(\lambda) d(\lambda)$$
(2.3.2)

$$Z = \int_{\lambda} \bar{z}(\lambda) E(\lambda) R(\lambda) d(\lambda)$$
(2.3.3)

where $E(\lambda)$ is the relative spectral radiant power distribution of an illuminant, $R(\lambda)$ is the spectral data of the signal and $\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$ are the colour matching functions.

The illuminant and reflected spectra are usually measured at every 10 nm or 20 nm interval from 400 nm to 720 nm. On the other hand, the colour-matching functions are given at every 5 nm or 1 nm interval. Interpolation is used during computation to estimate colour matching functions at every 10 nm interval.

Two colour signals having the same tristimulus values will look alike, when viewed under the same photopic conditions³³. This phenomenon is known as metamerism and is considered in a later section.

2.3.3 Chromaticity

Associated with any set of tristimulus values X,Y,Z are set of chromaticity coordinates x,y,z defined by equations 2.3.4, 2.3.5, and 2.3.6.

$$x = \frac{X}{X + Y + Z} \tag{2.3.4}$$

$$y = \frac{Y}{X + Y + Z} \tag{2.3.5}$$

$$z = \frac{Z}{X + Y + Z} \tag{2.3.6}$$

Chromaticity coordinates represent the relative amounts of tristimuls values. The chromaticity specifies the colour signal independent of its intensity. Hence colour signals with different spectral power distribution are represented by the same chromaticity⁶⁹. It is obvious that x + y + z = 1 and hence if x and y are known, z can always be deduced using 1 - x - y. With only two variables x,y, a two-dimensional diagram can be constructed.



This diagram is known as the chromaticity diagram as given in Figure 2.2.

Figure 2.2: CIE chromaticity diagram²⁶

It is characterized by a horseshoe shaped locus (spectral locus) of monochromatic spectral colours with a straight line connecting extreme short-wavelength and long-wavelength chromaticity coordinates. The central position is occupied by white and colours become more saturated as we move towards the edges. The unique property of this diagram is that the representative point of an additive mixture of two colour signals lie on a straight line passing through the chromaticity points corresponding to the constituents of the mixture⁶⁹.

2.3.4 Colour spaces and colour difference formulae

Chromaticity diagrams have many uses but as they show only proportions of tristimulus values and not their actual magnitudes, they are restricted to colours having the same luminance³³. They are also perceptually non-uniform. In 1976, the CIE defined two colour spaces. The first one is known as the CIELUV colour space and tends to be used with self-luminous stimuli such as those generated using additive colour-reproduction devices⁶⁴ and the second one the CIELAB colour space tends to be used for surface colour specification with coordinates (L^*, a^*, b^*) and is computed using Equations 2.3.7, 2.3.8 and 2.3.9:

$$L^* = 116 \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 \tag{2.3.7}$$

$$a^* = 500 \left[\left(\frac{X}{X_n} \right)^{\frac{1}{3}} - \left(\frac{Y}{Y_n} \right)^{\frac{1}{3}} \right]$$
 (2.3.8)

$$b^* = 500 \left[\left(\frac{Y}{Y_n} \right)^{\frac{1}{3}} - \left(\frac{Z}{Z_n} \right)^{\frac{1}{3}} \right]$$
(2.3.9)

where X, Y,Z are tristimulus values and X_n , Y_n , Z_n are tristimulus values of a white object colour stimulus. The coordinates L^* , a^* and b^* represent the lightness, rednessgreenness and yellow - blueness axes respectively. The lightness L* varies from 0 (black) to 100 (white). This non-linear transform of the X, Y,Z, values provided partial solutions to both the problems of colour apperance and colour difference⁶⁴. Two other quantities can be defined using the coordinates to form a cylindrical coordinate system. These are the hue h and chroma C^* given by Equation 2.3.10 and 2.3.11 respectively.

$$h = \arctan\left[\frac{b^*}{a^*}\right] \tag{2.3.10}$$

$$C^* = (a^{*2} + b^{*2})^{\frac{1}{2}}$$
(2.3.11)

It is possible to compute the colour difference for two colour signals in CIELAB colour space by calculating the Euclidean distance between the points that represent the signals in the space⁶⁴.

$$\Delta E_{ab}^* = \left[(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2 \right]^{1/2}$$
(2.3.12)

where

$$\Delta L^* = L_1^* - L_2^*$$
$$\Delta a^* = a_1^* - a_2^*$$
$$\Delta b^* = b_1^* - b_2^*$$

The subscripts denote the two colour signals. If we compute the colour difference using polar coordinates, equation becomes

$$\Delta E_{ab}^* = \left[(\Delta L^*)^2 + (\Delta C_{ab}^*)^2 + (\Delta H_{ab}^*)^2 \right]^{1/2}$$
(2.3.13)

Although the CIELAB colour space is more uniform than the tristimulus space it was created from, it is still far from being perceptual perfectly uniform⁶⁴. Consequently, for equal perceptual colour differences between pairs of samples, the values of CIELAB colour difference computed between points representing this pair in CIELAB colour space may vary by an order of magnitude⁶⁴. Since 1976, research work has been undertaken to produce more accurate and comprehensive colour difference formulae. These include the CMC colour difference formulae¹³, which was based upon the CIELAB colour difference components, CIE94 colour difference formulae⁶, which tried to overcome the complexity of the CMC formulae and lately the CIEDE2000³⁷, which is non-Euclidean colour difference formulae which corrects for the perceptual non-uniformity of the Euclidean colour difference formula in the CIELAB colour space.

2.3.5 Colour gamut

Digital colour imaging media provide a connection between digital data and colour signals. They are grouped into two classes namely output colour imaging media (e.g. monitors, projectors) which produce output colour signals based on digital data sent to it and input colour imaging media (e.g. cameras, scanners) which produce digital data based on sensing colour signals³⁹.

The definition of a digital colour imaging medium gamut depends on the class it belongs to. For output media, the colour gamut is the range of colour signals they can produce while for input media, it is the range of colour signals across which their responses show differences²⁰. For both classes, determining the gamut for a medium requires having access to the entire range of inputs to the medium. The colour gamut of an output medium is computed by sending the entire range of digital input (or a meaningful size of the input), measuring the corresponding output and computing the boundary enclosing these colours in a colour space³⁹. The generation of the range of input data is trivial because of its availability.

On the other hand, complexity arises when computing the gamut for input, media because it involves sampling the entire range of possible colour signals i.e. a set of colour stimuli with a gamut greater than or equal to the gamut of the input media is required to determine the range across which differences in stimuli can be sensed³⁹. Since the input gamut to be determined is not known, only the entire gamut of the colour stimuli is known to be greater than or equal to the gamut of the input media. Once a set of samples from the entire range of colour stimuli is available, their medium responses are obtained and used to determine the medium's gamut boundaries.

2.3.6 Metamerism

Metamerism is a phenomenon that arises when two colours match one another(same tristimulus value), but have different spectral composition. The eye responds to light as an integrated stimulation of each of the three cones types L,M,S³³. If two stimuli have identical L,M,S cone stimulations when seen under the same conditions, they will look alike no matter their spectral composition. For equal L,M,S cone responses to occur for two stimuli having different spectral power distribution, their curves need to have crossover points within each of the bands of the spectrum to which L,M,S cones are sensitive. It is therefore a characteristic of the metameric pairs that their spectral power distributions exhibit three or more crossover points in the visible spectrum³³. Metameric pairs are not defined as L,M,S cone responses but as stimuli that have the same tristimulus values⁶⁹.

In the colour industry, metameric pairs occur and it becomes imperative to know what extent these colours cease to match under the range of illuminants, observers and field sizes available in the industry. This is important because, the greater the degree of metamerism the greater the difference in spectral composition between a metameric pair, the greater the likelihood that the colours will no longer match one another if one of the matching parameters is altered such as, a change in the spectral composition of the illuminant, spectral sensitivity of the observer or field size³³. Since these differences are dependent on the illuminant, observer and field size, indices of metamerism can be computed for each case.

The CIE recommends that the degree of metamerism for change of illuminant is computed by calculating an Illuminant Metamerism Index M which involves calculating the colour difference between a metameric pair caused by substituting in place of a reference illuminant, a test illuminant having a different spectral composition. The colour difference formulae used should be stated. The preferred reference illuminant is the Standard Illuminant D_{65} . Test illuminant could be CIE Standard Illuminant A to represent tungsten light and fluorescent lamps represented by Illuminants F2, F7 or F11³³.

The CIE also recommends that the degree of metamerism for change of observer is evaluated by computing an Observer Metamerism Index M_2 or M_{10} , consisting of the size of the colour difference between a metameric pair caused by substituting in the place of a reference observer, a standard deviate observer (SDO) having different spectral sensitivities³³. The reference observer can either be the CIE 1931 Standard Colorimetric Observer (the 2° observer) or the CIE 1964 Supplementary Standard Colorimetric Observer (the 10° observer). A standard deviate observer (SDO) is obtained by modifying the CIE colour-matching functions of the reference observer.

An index of metamerism for change of field size has not been recommended by the CIE, but with the availability of two CIE Standard Colorimetric Observers such evaluation is possible for changes between 2° and $10^{\circ 33}$. For a pair of stimuli that are a metameric match for the CIE 1931 Standard Colorimetric Observer, their colour difference when computed using the CIE 1964 Supplementary Standard Colorimetric Observer can be used as metric of their metamerism for a change of field size.

CHAPTER THREE

HYPERSPECTRAL IMAGING

3.1 Introduction

Although multispectral imaging has been used for remote sensing applications since the early 1970s, hyperspectral imaging is finding increased relevance not only for remote sensing but for other applications in agriculture, physics, medicine, scientific research and surveillance. Multispectral imagers for example Landsat and Advanced Very High Resolution Radiometer (AVHRR), measure the reflectance of Earth's surface materials at a few broad wavelength bands separated by spectral segments where no measurements are taken. In contrast, most hyperspectral sensors measure reflected radiation as a series of narrow wavelength bands. The detailed reflectance spectrum acquired by hyperspectral imaging makes it possible to identify and distinguish material and conditions in ways that are impossible even with very high resolution multispectral imagery or colour imaging.

In this chapter, hyperspectral sensors and their applications in remote sensing, medicine, agriculture and scientific research are considered. Two remote sensing hyperspectral imagers using the whisk and push-broom design respectively are discussed. Hyperspectral imaging using electronically tunable filters is examined in detail, since such a system provided the experimental data for this thesis. Components of the imaging system like the monochrome CCD camera and tunable filter are also presented and a description of the technology surrounding them is given.

3.2 Applications

Hyperspectral imaging provides image data containing spatial and spectral information. The large amount of information available from hyperspectral imaging makes it attractive for use in many applications. The next few sections will discuss some of the uses of hyperspectral imaging in remote sensing, agriculture, medicine and research.

3.2.1 Remote sensing

In remote sensing, hyperspectral sensors use either the whisk-broom or push-broom design. In whisk broom sensors like AVIRIS (also referred to as across-track imagers) rotating mirrors are used to scan the scene from side to side perpendicular to the direction of the sensors platform just like a whisk-broom. The width of the sweep is referred to as the sensor swath. The rotating mirrors redirect the reflected light to a point where a single or just a few sensor detectors are grouped together. The moving mirrors create spatial distortions that must be corrected with pre-processing by the data provider before image data is delivered to the user. An advantage of whisk-broom imagers is that they have fewer sensor detectors to keep calibrated compared to its push broom counterpart.

Push broom sensors like Hyperion do not use rotating mirrors and can also be referred to as along-track imagers. The sensor detectors in a push broom design are lined up in a linear array. Instead of sweeping from side to side as the sensor system moves forward, the one dimensional sensor array captures the entire scan line at once like a pushbroom would. Pushbroom imagers are lighter, smaller and less complex because of fewer moving parts than whiskbroom imagers. Also they have better radiometric and spatial resolution. A major disadvantage of pushbroom imagers is the calibration required for a large number of detectors that make up the sensor system.

AVIRIS

NASA AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensor, is an optical sensor that captures images of the earth's surface spectral radiance in 224 bands approximately 10 nm spectral resolution covering the 380 - 2500nm spectral range. It has been flown on four aircraft platforms namely NASA's ER-2 jet, Twin Otter International's turboprop, Scaled Composites' Proteus, and NASA's WB-57⁴⁰. The ER-2 flies at approximately 20 km above sea level, at about 730 km/hr while the Twin Otter aircraft flies at 4km above ground level at 130km/hr. The main objective of the AVIRIS project is to identify, measure, and monitor constituents of the Earth's surface and atmosphere based on molecular absorption and particle scattering signatures. Research work carried out using AVIRIS data is focused on understanding processes related to the global environment and climate change⁴⁰. The AVIRIS contains 224 different detectors each with a wavelength sensitive range between 380nm and 2500nm of approximately 10 nm interval. When data from each detector is plotted, it produces a spectrum and comparing this resulting spectrum with those of known substances reveals information about the composition of the area being viewed by the sensor⁴⁰.(Figure 3.1).

Hyperion

The Hyperion hyperspectral imaging sensor flies on the NASA Earth Observing-1 (EO-1) spacecraft launched in late 2000. The EO-1 platform is in a 705-km sun-synchronous



Figure 3.1: AVIRIS data analysis

orbit following 1 minute behind LANDSAT 7, essentially viewing the same atmospheric conditions²³. The Hyperion sensor detects 220 10-nm hyperspectral bands between 400 nm (blue) and 2500 nm (mid-IR) and records reflectance in 12-bit format. The 30 m \times 30 m GSD of Hyperion mimics Landsat's spatial resolution; however, the 7.5 km hyperspectral swath is only a fraction of a 185-km wide Landsat scene. Another hyperspectral sensor aboard EO-1, called LEISA, with a 185-km swath at 250 m x 250 m GSD, collects 246 bands in the mid-IR portion of the spectrum where water vapor absorption is significant²³. These data were used to derive atmospheric correction information for the other sensor datasets.

3.2.2 Agriculture

The use of hyperspectral data in agriculture is growing quickly owing to improvements in the spatial and spectral resolution of hyperspectral sensors. Farming techniques are becoming more precise so that crop management is localised rather than being applied uniformly over the whole field. This requires detecting and identifying variable crop stress in monoculture plots. With hyperspectral images of these plots, local treatment like fertilisation, irrigation, insecticide can be applied which have implications on production cost and environmental management²¹,⁶¹. Crop libraries have also been developed for classification of different varieties of crops⁴⁹.

3.2.3 Medicine

The use of hyperspectral imaging techniques in medicine enables many characteristics of various tissues and organs in health and disease to be analysed which have not been previously investigated directly. This includes filter- based hyperspectral imagery used to capture dental samples and the human brain¹². Angelopoulou et al.⁴⁷ used a skin reflectance model to propose a method for skin detection under varying lighting conditions. Dicker et a.¹⁵ explored the use of hyperspectral imaging to determine the cell cycle status of live cells in culture. Dicker et al.¹⁶proposed a method which uses high resolution hyperspectral imaging to differentiate between normal skin and melanoma.

3.2.4 Research work

For colour- reproduction applications, the spectral and spatial complexity of natural scenes gives a major challenge during image accquistion and analysis. Natural scenes have colour gamuts that may extend beyond those of regular colour cameras which have constrained gamut and limited chromatic fidelity³⁹. The advantage of using hyperspectral sensors in this context is that images derived from them and their colour errors can be rendered faithfully without being constrained by the colour gamut available to a colour image-acquisition device, i.e. there is no limit on luminance, hue or chroma¹. Hyperspectral imaging has been used⁴² to determine whether spatial cone-excitation ratios are preserved under illuminant changes within the natural visual environment and in estimating the frequency of metamerism in natural scenes²⁴. These studies are relevant to some of the simulations considered later in this thesis.

3.3 Hyperspectral imaging with tunable filter

The capture of image cubes in stationary applications and rapid time-varying scenes can be accomplished using tunable filter hyperspectral imagers. A tunable filter imager, which is also a focal-plane imager, acquires an image at a single wavelength at a time. The spectral dimension is acquired by changing the tuning of the wavelength in time. The main components of this class of hyperpsectral imagers are a CCD camera, electronically tunable filter and lens system. The next two sections will look at the monochrome CCD camera and liquid crystal tunable filter and the technology behind them. Camera noise, which affects the overall quality of the final image, is will also be discussed.

3.4 CCD camera

Charge-coupled devices (CCD) were proposed in the 1970s as imaging sensors and are used for digital imaging. The CCD architecture has three basic functions, namely charge collection, charge transfer, and the conversion of charge into measurable voltage³². The



Figure 3.2: CCD basic structure

structure of a CCD is based upon metal-oxide-semiconductor (MOS) capacitor (Figure 3.2).

Charge is created when an external voltage is applied to the gate electrodes represented by P1, P2, P3. These charges are stored on photosensitive areas of the CCD and are then transfered to adjacent areas where it is converted. The gate electodes are usually made from highly conductive materials such as metal or polysilicon. The oxide layer is silicon dioxide and the channel is a semiconductor.

The sensor used for this work is an interline transfer sensor. Interline transfer CCD sensors consist of photosensitive sections comprising photodiodes and MOS structure diodes formed separately from the transfer section³². The charge produced by photoelctric conversion in a photodiode is stored in the photodiode junction capacitance. This charge is then transfered to the vertical shift register during the vertical blanking period through the transfer gate (Figure 3.3). Vertical shift registers are comprised of respective output



HORIZONTAL SHIFT REGISTER

Figure 3.3: Interline transfer CCD architecture

sections that also include horizontal shift registers. They are arranged along photodiode arrays so as to enclose each photodiode. The charge is transferred to the horizontal shift register for every line during the horizontal blanking period. Finally all charges reach the on-chip amplifier to be read out. Because the number of electrons collected in each sensor is proportional to the incident illumination level, the sensor typically has a linear response curve.

The camera used in the hyperspectral imaging system in this study is the low-noise Peltiercooled digital camera (Hamamatsu, model C4742-95-12ER, Hamamatsu Photonics K. K., Japan). It has a resolution of 1344×1024 pixels and the available exposure times range from 10 ms to 4200 s. It uses digital temperature compensation to reduce noise since it is Peltier-cooled. The intensity response at each pixel is recorded with 12- bit precision. The spectral range is from the ultra-violet to the infrared regions. The sensor used in the digital camera is a progressive-scan interline CCD with microlens which enables the camera to collect more photons from incoming light. It has an effective area of 8.66 mm \times 6.60 mm and sensor cell size 6.45 μ m \times 6.45 μ m (square pixels).

3.5 Camera noise

Camera noise can be seen as variations in pixel values that make the image a less than exact representation of the original scene. Camera noise can manifest itself in multiple ways. A classification of camera noise is given in Table 3.1. Camera noise is corrected for in most imaging systems by acquiring a dark frame which is an image captured with the camera objective closed. Noise compensation will be discussed in a later section.

3.6 Liquid crystal tunable filter

Liquid crystal tunable filters are based on the principles of birefringence and polarisation. Birefrigence is a behaviour exhibited by crystalline substances where the crystals display two different indices of refraction (double refraction) due to their anisotropic nature⁴⁷. Light wave being an electromagnetic wave has two distinct planes of oscillation for its electric and magnetic fields. Polarisation is associated with the electric field vector of a light wave. It is related to the geometry of light wave propagation. A light wave can be either unpolarised (rays having no preferred plane of oscillation) or polarised (all rays oscillating in a single plane). The process of converting unpolarised light to polarized is known as polarization and optical devices that achieve this are called polarisers. With polarised light, its plane of vibration can be rotated through a process known as retardation and the optical devices used are called retarders. When light enters a birefringent material, the process is modelled in terms of the light being broken up into the fast (called the ordinary ray) and slow (called the extraordinary ray) components (Figure 3.4). Because the two components travel at different velocities having refractive indices n_o and n_e , the waves get out of phase. The difference $\Delta n = n_e - n_o$ leads to a phase lag between the ordinary and extraordinary rays. When the rays are recombined as they exit the birefringent material, the polarisation state has changed because of this phase lag⁴⁷. For a birefringent

Noise type	Origin	Description	Dependencies
Photon shot noise	CCD sensor	Additive noise. Tempo-	Incident pixel
		ral and spatial variation in	illumination.
		output signal due to dis-	
		crete nature of electrons	
Dark current shot	CCD sensor	Additive noise. Tempo-	Temperature,
noise		ral and spatial variation of	exposure
		dark current electrons.	time.
FPN,Fixed-	CCD sensor	Additive noise. spatially	Temperature,
pattern noise		varying dark current den-	exposure
		sity for different pixels.	time.
PRNU,Photo	CCD sensor	Multiplicative noise. Spa-	Incident pixel
response non-		tial pixel-to-pixel varia-	illumination.
uniformity		tion.	
Thermal noise	CCD support IC	Additive noise. Tempo-	Temperature
		ral and spatial variation in	
		pixel values due to thermal	
		electrons.	
Reset noise	CCD support IC	Additive noise. Tempo-	Temperature,
		ral and spatial variation	CCD readout
		caused when charge is	rate.
		converted to voltage.	
On-chip amplifier	CCD sensor	Additive noise. White and	Temperature,
noise		1/f noise of voltage after	CCD readout
		charge conversion.	rate.
Off-chip amplifier	CCD support IC	Additive noise.White and	Temperature,
noise		1/f noise of amplifier and	CCD readout
		output.	rate.
Quantization	CCD support IC	Additive noise.uncertanity	Variance of
noise		in analog to digital con-	image data.
		verter .Image content de-	Sets lower
		pendent.	noise limit
			for non-trivial
			image content

Table 3.1: Camera noise classification³²

plate of thickness d, the phase lag between the two rays is given as

$$\delta = 2\pi d\Delta n / \lambda \tag{3.6.1}$$

where λ is the wavelength in vaccum. Example of birefringent materials used as retarders are liquid-crystal, quartz and calcite.

In a Lyot type design, the LCTF consist of a cascade of individual birefringent plates (sandwiched between polarisers) with each plate having twice the width of its immediate predecessor. Each individual stage consists of a birefrigent element fixed retarder (for example quartz plate), a variable retarder (for example nematic liquid crystal wave plate) and two linear polarisers. The linear polarisers are oriented such that their axes are paral-



Figure 3.4: Unpolarised light passed through a birefringent material

lel. The quartz element is oriented such that the extraordinary and ordinary components of the transmitted light are equal (Figure 3.5).

When a voltage is applied across the electrodes, an electric field is induced across the light path; a torque is exerted twisting the liquid crystal molecules into the direction of the electric field. A restoring force which tends to keep the molecules aligned parallel to the surfaces acting against the induced torque is produced such that the amount of twist is proportional to the strength of the electric field. As the molecules align closely to the electric field, the retardance through the liquid crystal plate decreases which produces a waveplate with electronically variable retardance.

Finally, a linear polariser selects wavelengths which have undergone an integral π phase shift through both retarders. This produces a transmittance which varies as $\cos^2(\delta_{\lambda})$, where δ_{λ} is the phase shift and was defined in Equation 3.6.1.

3.7 Noise Compensation

Correction for camera noise is a prerequisite for obtaining high resolution images in most imaging systems. Offset and thermal images are used during image processing. An offset image simply gives the response of the camera sensor when no light is entering the imaging system with little or no exposure time. It is the zero level of the CCD sensor. On the other hand, a thermal image is the signal from thermal charges accumulated during acquisition ³⁸. It is obtained by capturing an image with no light entering the objective using the same conditions as those for scene acquisition (same exposure time and temperature) and then subtracting the offset image (Figure 3.6). For this thesis, camera noise compensation was achieved by capturing images with the camera objective covered with a dark cloth using the same exposure time as scene acquisition. Thermal and offset images captured were only used for calibration analysis.


Figure 3.5: One stage liquid crystal tunable filter

3.8 Flat field correction

Flat-field correction is a technique used to improve quality in digital imaging. The aim is to remove artifacts from images that are caused by :

(1) Variations in the pixel-to-pixel sensitivity of the CCD sensor due to the photo-sensitive cells of the sensor having different quantum efficiency.

(2) Non uniformity of the illuminant.

(3) Effect of transmission through the imaging system (off-axis vinetting by liquid crystal tunalble filter)⁴².

Correction is achieved by capturing the image of a smooth, matt, white card with a surface uniformly illuminated during the acquisition stage. A dark image is also captured as described in the previous section. These images are also saved for use during image



Figure 3.6: Offset image captured at wavelength of 550 nm

processing. In Figure 3.7, a flat-field image can be seen.



Figure 3.7: Flat field image accquired at 550 nm

3.9 Stray-light compensation

In optical imaging systems, stray-light is considered as light in the optical path that is imaged on the sensor but does not originate directly from the captured object³¹. It could be caused by the optical filters and the geometry of the camera. These include Fresnel reflection from lens-elements and filter surfaces, diffraction at aperture edges, surface imperfections, dust and other particles³⁴. Stray-light adds a noticeable offset to pixel values and this degrades both image contrast and measurement accuracy so there is a need

to compensate for these effects. Jansson and Breault³⁴ proposed a stray-light model based on the convolution of the image data with a point spread function which characterises the effect of stray-light for each pixel.

For simplicity they considered, a line scanner in which only one spatial axis requires consideration. The finite-extent two-dimensional case can also readily be formulated with one independent variable. Let S(x, x') be the PSF of such a scanner in which the flux received by a detector having coordinate x along an image line is given by Equation 3.9.1.

$$I(x) = \int S(x, x')O(x')dx'$$
 (3.9.1)

where O(x') is the flux emanating from points along some object line having coordinate x'. The compensation is done by solving Equation 3.9.1 for O(x') using an iterative Van Cittertt method algorithm³⁴. This method works well for locally limited point spread functions.

Helling³¹ modelled stray light as a superposition of brightness which is a function of image data but not as a locally limited problem. It is considered to be spatially dependent and is a linear function of the image data. From his experiments, it is shown that stray-light can affect opposite portions of the captured image³¹. The measured signal $I_{x,y}$ for pixel (x, y) affected by stray-light for one wavelength channel can be given as

$$\tilde{I}_{x,y} = \int (P_{x,y}(\lambda)r_{x,y}(\lambda) + \hat{S}_{x,y}(\lambda))\tau(\lambda)d\lambda$$
(3.9.2)

where $P_{x,y}(\lambda)$ is the power spectrum of the light source, $r_{x,y}(\lambda)$ is the spectral reflectance function of the imaged object, $\hat{S}_{x,y}(\lambda)$ is the spectral distribution of the stray light and $\tau(\lambda)$ is the spectral sensitivity of the imaging system. Equation 3.9.2 can be represented as

$$\tilde{I}_{x,y} = I_{x,y} + \hat{I}_{x,y}$$
(3.9.3)

where $I_{x,y}$ is original signal not affected by stray-light and $\hat{I}_{x,y}$ is the offset value introduced by straylight. Terms with spatial dependency carry indices (x, y) indicating the position of a pixel.

Stray-light compensation is then achieved by extracting the original signal $I_{x,y}$ from the measured signal $\tilde{I}_{x,y}$. The offset signal $\hat{I}_{x,y}$ for pixel (x, y) is modelled as the contribution of all stray-light offsets from all pixels (x_o, y_o) in the image and is given in Equation 3.9.4

$$\hat{I}_{x,y} = \sum_{x_o} \sum_{y_o} k_{x,y,x_o,y_o} I_{x_o,y_o}$$
(3.9.4)

where k_{x,y,x_o,y_o} are called coupling coefficients and give the correlation between pixels³¹. These coefficients give the ratio of the pixel value I_{x_o,y_o} that appears as straylight at pixel $\hat{I}_{x,y}$.

The memory requirements for computing these coupling coefficients will be enormous if



Figure 3.8: Stray light image for 550 nm

we consider say an image with spatial resolution of 1024×1344 pixels. For this thesis, images were divided into sub-regions (4 rows and 6 columns) and the mean of each region was computed resulting in an image containing 24 pixels. Each image produces a total of 576 coupling coefficients. Helling has shown that measurement of coupling coefficients using sub-sampled images is sufficient for stray-light compensation³¹.

Coupling coefficients are obtained by carrying out a series of measurements. A black reference $\tilde{B}_{x,y}$ is captured first. A sub-sampled image $\tilde{B}'_{x,y}$ is produced using the procedure outlined earlier. A white rectangular patch matching the size of each sub region is then placed in turn at each sub-region and captured producing $\tilde{I}_{x,y}$. Their sub-images are also obtained. Figure 3.8 shows a white patch captured at one of the sub-regions.

The coupling coefficient are then computed using Equation 3.9.5

$$k'_{x,y,x_{o},y_{o}} = \frac{\tilde{I}_{x,y} - \tilde{B'}_{x,y}}{\tilde{I}_{x_{o},y_{o}} - \tilde{B'}_{x,y}}$$
(3.9.5)

where $\tilde{B}'_{x,y}$ is the sub-sampled image of the black reference, $\tilde{I}_{x,y}$ is the value of the sub-image at pixel position(x, y) and \tilde{I}_{x_o, y_o} is the value of the sub-sampled image at the position the white patch was placed. The case where $(x_o, y_o) = (x, y)$ presents a problem as this describes the stray-light contribution from its own position. The average value of neighbouring coefficients is used for this position.

Once the coupling coefficients are known, images can be compensated for stray-light using Equation 3.9.4 to compute the stray-light offset and then subtract the result from the measured signal.

3.10 Image Registration

When images taken at different times by different sensors or from different viewpoints need to be compared, a problem arises as these images need to be aligned to compare or integrate data between them. Image registration is the process of aligning (overlapping) two or multiple images of the same scene captured under different imaging conditions. It is a crucial step in most image evaluation tasks where the final image is a combination of images from various sources or images were acquired at different times, as is the case in hyperspectral imaging.

Image registration is required in remote sensing (multispectral and hyperspectral classification, weather forecasting, creating super-resolution images, integrating information into geographic information systems (GIS), in medicine (combining computer tomography (CT) and NMR data to obtain the complete information about the patient, monitoring tumour growth, treatment verification, and in computer vision (target localisation, automatic quality control). Image registration methods can be grouped according to image acquisition methods.

Multi-view analysis Images of the same scene are acquired from different viewpoints. The objective is to gain a larger 2D or 3D representation of the imaged scene. In computer vision, it is used for shape recovery and in remote sensing for mosaicing of images of a surveyed area.

Multi-temporal analysis Images of the same scene are acquired at different times, during regular intervals and sometimes under different imaging conditions. The aim is to discover and evaluate changes in the scene which appear between image acquisitions. It is used in remote sensing for landscape planning and in computer vision for automatic change detection and motion tracking. It also finds use in medical imaging where it can be used for monitoring of healing therapy and tumour evolution.

Multi-modal analysis Images of the same scene are acquired by different sensors. The aim is to combine information obtained from different sources to gain a detailed scene representation. It is used in medical imaging for integration of sensors recording of magnetic resonance image (MRI), ultrasound or CT with sensor readings of positron emission tomography(PET) or magnetic resonance spectroscopy(MRS) and results are used in radiotherapy and nuclear medicine. The hyperspectral images considered in this thesis fall under this category as each individual wavelength channel can be taken to represent a different sensor.

Due to the various types of images to be registered and the different type of image degradation present, there is no general method applicable to all registration tasks. Methods applied should not only consider the geometric deformation between images but also consider noise, radiometric deformations, required registration accuracy and applicationdependent data properties. Most image registration methods consist of four steps. These are feature detection, feature matching, mapping function estimation and image resampling and transformation⁷¹. Registration methods can be grouped into area-based and feature-based. Area-based methods skip the feature detection step and emphasis is on feature matching. Featured-based methods on the other hand rely heavily on the feature detection stage. In the next section, each step is analysed and the methods associated with it.

3.10.1 Feature detection

Distinctive objects e.g. edges, contours, corners and closed boundary regions are manually or automatically detected, Their point representatives(centre of gravity, line endings, distinctive points) are normally used and are known as control points. The choice of these so called control points is not trivial as they have to be spread over the image and can be easily detected. The detected feature set in the reference and sensed image must have common elements, even when both images do not cover the entire scene or have object occlusions.

Significant regions, lines and points in the image are regarded as features. They should be distinct and stable over time to stay at fixed positions during image acquisition. Region features are detected using segmentation methods. The regions are usually represented by their centre of gravity, which is invariant with respect to rotation, scaling, skewing and also stable under noise and image intensity variation. Line features seen as general line segments can be detected using standard edge- detection methods. A survey of edge-detection methods is given in ³⁶. In point -features detection, a point is defined as a line intersection, centroid of closed-boundary region or local modulus maximum of the wavelet transform.

3.10.2 Feature matching

Detected features in the image to be registered (sensed image) and reference image can be matched using image intensity values, feature spatial distribution or feature symbolic description. Feature matching methods can be grouped again into area-based and feature methods.

Area based methods merge the feature- detection and matching steps. They are applied when the images do not have many prominent details and the distinctive information for matching is provided by image intensity rather than local shapes and structures. It deals with images without attempting to match distinct objects in the image. Windows of predefined size or sometimes the entire images are used to establish correspondence during feature matching^{50, 5, 48}. Area based image registration can be achieved using normalized cross correlation⁷¹. Cross correlation is computed for window pairs or the whole image from the sensed and reference images and the maximum overlap between images is found. The Cross correlation-based registration aligns mutually translated images and ones with some scaling and rotation present. They can be sensitive to intensity changes included by varying illumination, noise or the use of different sensors. Other area- based methods include fourier methods^{9, 10, 67, 4}, mutual information methods^{63, 51} and optimisation methods^{63, 71, 55}.

Feature- based methods require that two sets of features in the reference and sensed images which are represented by their control points (CP) have been detected. A pairwise correspondence is then found between them using their spatial relations or various feature descriptors.

Methods which employ spatial relations among features are used when the detected features are imprecise or if there is distortion in the neighbourhood of the detected feature. Stockman et. al.⁵⁸ use clustering techniques to match points connected by abstract edges or line segments. Goshtasby et. al²⁸ achieves registration using a graph- matching algorithm which estimates transformation parameters.

Feature descriptors in the sensed and reference image can be used during the feature matching step. They need to fulfil certain conditions. These descriptors should be invariant to image deformation and noise, unique, stable and independent⁷¹. Usually not all these conditions can or need to be satisfied simultaneously. There is usually a tradeoff depending on the type of image being registered. Features from the sensed and referenced images with the most similar invariant descriptors are paired as the corresponding ones. The choice of the type of the invariant description depends on the feature characteristics and estimated geometric degradation of the images. The simplest feature description is the image intensity itself limited to the close neighbourhood. The Correlation coefficient as used by Zheng and Chellapa⁷⁰ assumes geometric deformation and compensates by estimating the illumination direction and then performing coarse-to-fine correlation based registration⁷⁰.

3.10.3 Transform model estimation

Once the feature correspondence has been established, the next step is constructing a mapping function. This function should transform the sensed image and align it to the reference image. The type of mapping function used should correspond to the geometric deformation of the sensed image, method of image acquisition and the required accuracy of the registration. Mapping models can be classified into two main groups namely global and local mapping models⁷¹. Global models use all the control points for estimating one set of mapping function parameters while local mapping models handle the image as a combination of patches and define mapping function parameters for each patch separately⁷¹.

One common global mapping model uses bivariate polynomials of low degrees. The transformation consist of rotation, translation and scaling only. This model is sometimes known as a shape- preserving mapping because it preserves angles and curvatures. An-

other global model is the affine transform. It is also a linear model which can map a parallelogram onto a square. It is determined by three non-collinear control points and preserves straight lines and straight- line parallelism⁷¹.

Images that are deformed locally cannot be mapped using global- mapping models. Local areas of the image should be registered with the available information about local geometric distortion. Some local mapping models have been used by Goshtasby²⁷, Ehlers and Fogel¹⁸, Wiemker⁶⁵ and Flusser²². The weighted least- square and weighted mean methods²⁷ register images locally by introducing a slight variation to the original least- square method.

3.10.4 Image resampling and transformation

The mapping functions are used to transform the sensed image. This transformation can be achieved using a forward or backward method⁷¹. In the forward method, each pixel from the sensed image is directly transformed using the mapping functions. This method is difficult to implement as it produces holes and/or overlaps in the output image due to discretisation and rounding. On the other hand, for the backward method, the registered pixel data from the sensed image are determined using the coordinates of the target pixel (the same coordinate system as that of the reference image) and the inverse of the estimated mapping function. Image interpolation takes place in the sensed image on the regular grid. In this way neither holes nor overlaps can occur in the output image. Image interpolation is accomplished by convolution of the image with an interpolation kernel.

3.11 Image Processing

Normalisation of raw hyperspectral images involves compensating for straylight, noise, non-uniformity of illuminant and transmittance variations of the tunable filter. The normalised image for each wavelength $C_{(\lambda)}$ is obtained using the model presented in Equation 3.11.1

$$C(\lambda) = \frac{I_r(\lambda) - I_o(\lambda) - I_{tr}(\lambda)}{I_f(\lambda) - I_o(\lambda) - I_{tf}(\lambda)} \times K_\lambda$$
(3.11.1)

Where $I_r(\lambda)$ is the raw tiff image, $I_o(\lambda)$ is the offset image, $I_{tr}(\lambda)$ is the thermal image associated with the raw image (acquired using the same conditions), $I_f(\lambda)$ is the flatfield image, $I_{tf}(\lambda)$ is the thermal image associated with the flat-field image and K is a wavelength dependent normalization coefficient which mirrors the mean value of the flat-field image.

The normalised image $C(\lambda)$ is then compensated for straylight using coupling coefficients as explained in the section on straylight. Image registration is also carried out. The final image is then used to obtain the spectral reflectance or radiance of surfaces in any given scene.

3.11.1 Spectral reflectance

The spectral reflectance $R(\lambda)$ for each pixel is obtained by normalizing the corrected image $C_i(\lambda)$ at each pixel against the reference materials (Munsell chips) placed within the scene. Equation 3.11.2 shows the mathematical expression where P_{ref} is the mean value of a selected patch on the reference material and R_g is the spectrum of the reference material

$$R(\lambda) = \frac{C_i(\lambda)}{P_{ref}} R_g \tag{3.11.2}$$

3.12 Hyperspectral Imaging system performance

The basic method used for quantifying the performance of imaging systems is by estimating the quality of images produced. This can be achieved by computing the modulation transfer function (MTF) of the system. The MTF is a performance measure of an imaging system describing its ability to resolve signals at different spatial frequencies¹⁷. It is an important image quality metric that has applications in almost every major imaging science application. Different methods are used to determine the MTF of imaging systems based on slit, bar patterns and edge images. Measurement of MTF using slit images is a time-consuming alignment procedure and the overall setup required for these measurements are expensive⁶⁰. Bar patterns are not the best choices since the determination of the modulation of digital bar patterns is not trivial. Edge images on the other hand produce high accuracy even at low spatial frequencies and this is useful for imaging systems where spatial frequencies required are defined up to the Nyquist limit of the detector as aliasing (folding of spatial frequency components above Nyquist frequency into frequencies below the Nyquist frequency) becomes dominant at higher frequencies. The edge method was used for this research because of the advantages stated above. Modulation transfer functions are computed from line spread functions (LSF) or edge spread functions (ESF). Their relationship is considered in the next section.

3.13 MTF, ESF and LSF

The line spread function can be described as the output of the imaging system for an ideal line. It is usually very tedious to acquire the line spread function directly from the image so an edge spread function is first constructed and its derivative gives the line spread function. For an ideal imaging system, a step function (high contrast edge) will not be degraded. The line spread function of an ideal imaging system can be expressed

mathematically as a delta function². A step function i(x) is defined as follows :

$$i(x) = \begin{array}{cc} 0 & \text{when } x < 0\\ 1 & \text{when } x \ge 1 \end{array}$$
(3.13.1)

A linear system gives an output o(x) which is equal to the convolution of the input signal i(x) with the LSF of the system:

$$o(x) = i(x) * L(x) = \int_{-\infty}^{\infty} L(\alpha) \cdot i(x - \alpha) \, d\alpha \tag{3.13.2}$$

Since the input i(x) is a step function, the output o(x) is the edge spread function represented as E(x). From Equation 3.13.2, when $(x - \alpha)$ is < 0, i(x) = 0 and for all other values i(x) = 1. E(x) is then given as

$$E(x) = \int_{x}^{\infty} L(\alpha) \, d\alpha \tag{3.13.3}$$

The derivative of equation 3.13.3 gives the formula for the LSF:

$$L(x) = \frac{dE(x)}{dx} \tag{3.13.4}$$

The modulation transfer function M(v) of a system is calculated by taking the Fourier transform of a line spread function (LSF).

$$M(v) = \int_{-\infty}^{\infty} L(x) . e^{-i2\pi vx} dx$$
 (3.13.5)

3.13.1 Edge Estimation

The initial step in the construction of an edge spread function is identifying a high contrast sharp edge region in an image. Most digital image acquisition devices are designed to undersample⁵⁶. This property of imaging devices can reduce the accuracy of edge spread function measurements since undersampling causes aliasing. The use of the slanted- edge algorithm solves this problem. A step edge is slightly tilted perpendicular to the scan direction. This makes super-resolution measurements possible and uses the change in phase of the edge across the sampling grid to create a super-resolved ESF¹⁷. Figure 3.9 shows a slanted edge image with a tilt angle of 3°.

The next step requires the estimation of the edge location for each scan line (rows) of the slanted edge image. There are different methods used for estimating the edge location in each row to sub-pixel accuracy. Buhr et. al¹⁷ used linear interpolation to determine the edge estimates. A straight- line fit of individual edge estimates is then computed using linear regression. Granfors et. al²⁹ used a least-squares fitting algorithm to fit a straight line to the edge locations using 20 data points around an initial estimate of the edge



Figure 3.9: Slanted edge image with tilt angle of 3°

position and then performing a final fit using 20 data points around the first fit. Saunders et. al⁵⁴ used a Sobel detector to compute the angle of the edge line by using a double Randon transform.

In the work reported here, estimates were made of both the edge location and direction and was based on the algorithm proposed by Buhr et.al¹⁷. The edge locations were estimated to sub-pixel accuracy by computing the derivative of elements in each row using a Frequency response impulse (FIR) filter which uses the central difference method to accomplish its task. The centroid for each row is then computed by calculating the weighted sum of pixels in a row and then dividing by the sum of all pixels in that row. For example, let *X* represent a vector of pixels in a row of an edge image.

$$X = [x_1, x_2, x_3, \dots, x_n]$$
(3.13.6)

The centroid c is computed using Equation 3.13.7

$$c = \frac{x_1 + 2x_2 + 3x_3 + \dots + x_n}{x_1 + x_2 + x_3 + \dots + x_n}$$
(3.13.7)

Linear regression is then used to fit a straight line through individual edge locations and the slope and intercepts are obtained. The equation for the linear fit to the set of centroid data is expressed as the inverse of the regular linear equation⁴⁶

$$x = a + b(y - 1) \tag{3.13.8}$$

where x is the x-direction (pixel) location, y is the y-direction line number, a is the location of the edge on the first row of the edge image and b is the slope of the fit. The plot of the linear fit for an hyperspectral edge image obtained at 560 nm is given in Figure 3.10.



Figure 3.10: Linear fit for slanted edge profile obtained from image acquired at 560 nm

3.13.2 Edge Spread Function

The edge spread function can be constructed using different techniques. Samei et. al⁵² and Saunders et. al⁵⁴ accomplished their task by projecting the edge image data along the edge transition angle they derived using double Hough and double Randon transformations methods respectively. Granfors et. al²⁹ binned the pixel values according to their distance from the edge position with a bin size of between 5% and 10% of the pixel pitch and the average pixel value is calculated for each bin and this makes up the edge spread function. Buhr et. al¹⁷ based their ESF construction on the number N of lines (rows) that produce one pixel shift of the edge. An oversampled edge spread function is then produced using N consecutive lines to form the edge image. One of the methods adopted for this research is similar to the one used by Buhr et. al. It is not only robust but also very simple to implement and produces accurate results. Figure 3.11 shows a graphical description of the setup.

The tilt angle is represented by α . The sampling distance between neighbouring pixels is given by p. A slight shift of the sampling positions from line to line due to the edge tilt Δx is given in Equation 3.13.9 as

$$\Delta x = p \tan \alpha \tag{3.13.9}$$

The consecutive number of lines needed for a shift of the edge by one pixel is obtained



Figure 3.11: Graphical description of edge spread function computation¹⁷

by dividing the sampling distance by the edge shift.

$$N = p/\Delta x = 1/\tan\alpha \tag{3.13.10}$$

One of the most important steps of this algorithm happens to be the determination of the integer N. This can be obtained using Equation 3.13.10, if the angle of tilt is known. On the other hand, if the angle is not known, N can also be obtained from the slope b of the regression line earlier computed when the edge locations for each row were determined:

$$N = 1/b$$
 (3.13.11)

The inverse of the slope (rounded up to the nearest integer) gives the lateral shift of the edge by a pixel¹⁷. This gives the number of rows needed to form a super- sampled edge spread function. The super-sampled edge spread function is easily obtained by rearranging the pixels in the region of interest into a vector. The first pixel in the first row becomes the first entry in the super-sampled edge spread function. The next entry is the first pixel in the second row and this goes on until all the pixels in our edge profile are rearranged. This method uses an assumption that the data points in the super sampled edge spread function are sampled edge spread functions.

distance is given in Equation 3.13.12 as

$$d = a/N \tag{3.13.12}$$

where a is the original sampling distance and N is the number of rows needed for a lateral shift of one pixel obtained using Equation 3.13.11.

3.13.3 Line Spread Function

The edge spread function is fitted using a least-square regression function. It uses an algorithm that iteratively reweighs response values and recomputes least-square fits. The ESF fit is then differentiated and this gives the line spread function (Figure 3.13). Figure 3.12 gives an oversampled edge spread function constructed from a high contrast edge for an edge image captured at 560 nm. The MTF is obtained by computing the Fourier transform of the line spread function.



Figure 3.12: Edge spread function

The MTF is obtained by computing the Fourier transform of the line spread function(LSF).



Figure 3.13: Line spread function

CHAPTER FOUR

SYSTEM CALIBRATION

4.1 Introduction

The characterization of any hyperspectral imaging system is crucial to obtaining high resolution images. For scientific research and other applications where accurate light measurement is required, the performance of the imaging system must be checked to ensure reliable data is produced.

This chapter deals with the calibration and characterization of a focal-plane hyperspectral imaging system. The hyperspectral imaging system used for acquiring images for this thesis is discussed. Input- output and modulation transfer functions are computed to investigate linearity of the imaging system and image quality respectively. Analysis of system noise, vignetting and straylight which affect image quality is discussed. Hyperspectral image registration algorithms are presented and their accuracy is evaluated using edge tracking. Finally, calibration verification is tested on Gretag Macbeth colour checker chart hyperspectral images.

4.2 Hyperspectral Imaging System

The system used for this work consisted of a Peltier- cooled CCD camera and a liquid crystal tuneable filter electronically controlled by computer software. The liquid tuneable filter is mounted in front of the lens with an infra-red blocking filter (Figure 4.1).

The camera is a low-noise Peltier-cooled digital camera (Hamamatsu, model C4742-95-12ER, Hamamatsu Photonics K. K., Japan). It has a resolution of 1344×1024 pixels and the available exposure times range from 10 ms to 4200 s. It uses digital temperature compensation to reduce noise since it is Peltier-cooled. The intensity response at each pixel is recorded with 12-bit precision. The spectral range is from the ultra-violet to the infra-red regions. The sensor used in the digital camera is a progressive-scan interline CCD with microlens which enables the camera to collect more photons from incoming light. It has an effective area of 8.66 mm × 6.60 mm and sensor cell size 6.45 μ m× 6.45



Figure 4.1: Hyperspectral Imaging system

 μ m (square pixels).

The liquid crystal tuneable filter (LCTF) is a VariSpec, model VS-VIS2-10-HC-35-SQ, Cambridge Research and Instrumentation. It is mounted in front of the camera lens. The filter has an aperture of 35 mm and the whole imaging system has a field of view of $\pm 7^{\circ}$. The wavelength of peak transmission could be varied over a range spanning 400 nm - 720 nm with a full width at half-maximum transmission of 10 mm at 550 nm, decreasing to 6 mm at 400 nm and 16 mm at 720 nm. The spectral transmittance of the filter when varying the peak wavelength in 10 nm intervals from 400 nm to 720 nm was measured using a monochromator. Figure 4.2 shows the transmittance curves for selected wavelengths (400 nm, 490 nm, 560 nm, 640 nm, 720 nm).

As can be seen from Figure 4.2, the shorter wavelength data becomes noisy after the visible spectrum. This is caused by the sensitivity of the detector inside the monochromator to these wavelengths.

The characterisation of the LCTF was done by plotting the nominal peak-transmission wavelength as recorded by the monochromator against the actual peak-transmission wavelengths. A Gaussian fit was first applied to the transmittance curves of the liquid crystal tunable filter measured using the monochromator to obtain peak nominal wavelengths. Figures 4.3 and 4.4 show the plot of nominal against actual wavelength peak-transmission values and Gaussian fit for 550 nm and respectively.



Figure 4.2: Spectral transmittance of LCTF measured using a monochromator

4.2.1 Nominal wavelength accuracy

Analysis was done to determine if the nominal wavelengths selected by the liquid crystal tunable filter and used to capture hyperspectral images are accurate. The experimental set up involved capturing images of a mercury vapour lamp. Mercury vapour lamps have principal emission lines in the visible spectrum⁶⁹. Two of these lines were investigated (436 nm and 546 nm). The first set of images were captured between 420 nm and 448 nm with a 4 nm interval and the second batch were between 528 nm and 560 nm also having a 4 nm interval. Images were then normalised by subtracting the dark noise images and dividing by the analog camera gain and exposure time. Regions (100 x 100 pixels) from the image namely the centre, top right corner, middle up and top left corner were extracted, averaged and a Gaussian fit was applied. Figure 4.5 and 4.6 show the Gaussian fit of the central region images acquired at the short and middle wavelengths respectively .

Table 4.1 gives the peak wavelength values from the Gaussian fit which represent the principal lines being investigated at various locations in the image. From these results,



Figure 4.3: Plot of nominal peak wavelength against actual peak wavelength



Figure 4.4: Gaussian fit of filters transmittance curve at 550 nm

the principal line found in the shorter wavelength region had a maximum variation of 0.6 nm while the line from the middle wavelength region had a maximum variation of 0.9 nm. These results are less than 1 nm and were deem accurate for further research work.

4.3 Acquisition

The process of obtaining high resolution hyperspectral images involves multiple stages. Images are generally captured by pointing the hyperspectral imaging system (CCD cam-



Figure 4.5: Gaussian fit of central region for short wavelengths (420 nm - 448nm)



Figure 4.6: Gaussian fit of central region for middle wavelengths (528 nm - 560nm)

Image location	Line 1peak Wavelength, nm	Line 2 peak Wavelength,nm
Centre	436.6	546.9
Top right corner	436.5	546.8
Top left corner	436.6	546.9
Middle up	436.6	546.5

Table 4.1: Mercury vapor lamp principal lines peak wavelength

era with a tunable filter mounted on it) to a scene of interest, adjusting the focus and zoom of the CCD camera, and recording the sequences. The wavelength range used is 400 nm - 720 nm at a 10nm interval hence providing 33 images in each image sequences. Neutral grey reference materials are inserted into the scene and are used for computing the effective spectral radiance and reflectance functions of each pixel in the scene. Figure 4.7 shows N2.5,N5 and N7 Munsell chips used during image acquisition.



Figure 4.7: Munsell reference chips

Bespoke algorithms are used to automatically determine the exposure time of the imaging system before acquisition so that maximum pixel output is within 80%-90% of the CCD saturation value. The spectrum of light reflected from the munsell chips are recorded immediately after acquisition by a telespectroradiometer (SpectraColorimeter, PR-650, Photo Research Inc. Chatsworth, California). For natural scene imaging, care was taken not to capture spectral images when there is movement in the scene.

4.4 Input-output function

An important property of imaging systems is its linearity in response to incident light. In hyperspectral imaging systems using charge-coupled device (CCD) sensors, the basic function of the CCD is to convert photons carrying image information into an electronic signal³². After digitization, the signal output should ideally be linearly proportional to the amount of light incident on the sensor.

A transfer function relating the number of photons incident on the sensor and the digital output is determined by a multi-stage process which involves the creation and transfer of charge carriers (electron-hole pairs) in the active pixel regions, followed by conversion of electrons from the charge domain into the voltage domain as an amplified voltage signal as stated in chapter three. The transfer function results in a linear variation of final digitized

output signal in relation to the amount of light incident on the CCD, such that the output signal is equal to the photon input multiplied by a proportionality constant(gain)³².

The linearity of a camera system is determined by the CCD itself, as well as other electronic components in the signal processing chain. In effect, any nonlinearity indicates a change in the camera's gain constant with signal level. Quantitative imaging operations, rely on absolute signal measurements, and require that there be no significant interdependence between camera gain and signal intensity. Scientific CCD imaging systems exhibit extremely good linearity over a wide signal range but when full well conditions are reached under high illumination intensity, a nonlinear response is usually observed³². If overall illumination is sufficiently bright, the CCD response becomes nonlinear. Depending upon the sensor characteristics, nonlinear response may also result under extremely low illumination levels.

A common technique for assessing linearity is based on a graphical plot of measured output signal as a function of exposure time, extending to the full well capacity of the device (the number of electrons held by a potential well or pixel; also referred to as linear full well)³². This metric may be defined as a percentage of deviation from linearity in comparison to the maximum signal intensity obtained at full well conditions.

The linearity of the hyperspectral imaging system was investigated by recording an outputinput function using a neutral density wedge, a diffuser, a beam splitter and a quartzhalogen bench lamp. This process involved measuring the signal captured by the hyperspectral imaging system and also recording the luminance using a luminance meter (LMT).

The diffuser was positioned over the aperture of the CCD camera while the neutral density wedge was placed in front of the quartz- halogen lamp and acted as a mask having a density which increases exponentially along its length. A 50/50 beam splitter made of two triangular glass prisms was placed between the light source and the hyperspectral imaging system with the camera capturing the half the signal and the LMT recording the other half (Figure 4.8).

Images were captured at fixed wavelengths (450 nm, 550 nm and 650 nm) as the neutral density wedge was adjusted in steps. A total of 24 steps were used ranging from bright illumination to very low light levels. The LMT data were recorded simultaneously. The LMT data were then corrected for reflection-transmission properties of the beam splitter by recording LMT readings from the hyperspectral imaging system position and using a linear regression fit to define a relationship between LMT data as seen by the hyperspectral imaging system and the original LMT data collected. The experiment was performed twice. In the first set, an analog gain factor of 100 units was introduced while the second set had no analog gain. Mean signal values with pixel patches of 5×5 , 20×20 , and 790×870 were then used to investigate linearity (Figure 4. 9). These values were plotted against the normalized LMT data and the plot for 550 nm without any gain factor is given



Figure 4.8: Input-output function experimental setup

in Figure 4.10.



Figure 4.9: Test image showing 20×20 and 790×870 pixel patches

Results show the hyperspectral imaging system is linear for average light levels but the same could not be said about low light levels as the data points were too close together. This can be attributed to the property of the neutral density wedge where the density varies exponentially with length hence no significant difference as the light level reduces. An exponential fit was used to analyse the behaviour of the neutral density wedge (Figure 4.11).

Figure 4.11 shows that an exponential curve fits the data accuquired using the neutral density wedge indicating the hyperspectral imaging system shows some linearity in low light levels.



Figure 4.10: Mean signal of HSI camera against Source Luminance for 550nm



Figure 4.11: Exponential fit of Mean signal of HSI camera against Source Luminance for 550nm

4.5 System noise characterization

The input-output function analysed in the previous section gives an indication of the linearity of the hyperspectral system but it is important to quantify the spatial variation in the sensitivity of the imaging system. In principle, the input-output data could be used for this analysis but this is not trivial, since there is no means of quantifying the spatial uniformity of the light source. One of the aims of this characterization was to check for

systematic variation from image to image in the captured series. This will help in understanding if averaging replicate images are useful or not. When averaging images, the noise is assumed to be zero mean Gaussian noise. Lowpass filtering an image or averaging two images may destroy details in the image. In order to avoid this and to improve the averaging technique, Mansouri et.al³⁸ acquired 6 images instead of 2 for each channel and the same process was used for this work.

4.5.1 Dark noise image

Six repeated acquisitions of dark noise images were carried out under identical conditions. A slice was then taken through the centre of each image producing intensity profiles. The slices were taken from the centre for all six images. The intensity profiles are plotted against their respective row or column sizes with one trace below the other (all six). Figure 4.12 and 4.13 show the horizontal and vertical intensity profile plots for dark noise image acquired at 500 nm using camera aperture setting 5.6.



Figure 4.12: Horizontal slice of dark noise image captured for aperture 5.6



Figure 4.13: Vertical slice of dark noise image captured for aperture 5.6

From Figures 4.12 and 4.13, it can be seen that the fluctuations in all six images show no systematic variation which implies that an averaged image could be used for all subsequent acquisitions.

The other aim was analysis of the relationship between the cameras noise and exposure time. This analysis should give an idea of the contribution of dark current as a function of exposure time.

Eight repeated acquisitions of a single wavelength (550 nm) dark noise image under identical conditions were done for aperture setting 5.6 and a focus setting of infinity. The exposure time ranged from 0.1 s to 30 s. The analog gain factor of the CCD camera was set to zero.

A plot of mean dark noise images against exposure time is given in Figure 4.14. It can be seen from this figure that the mean dark noise is almost constant over the range of



Figure 4.14: Plot of mean dark noise signal against exposure time

exposure time used. This can be attributed to the Peltier cooling property of the CCD camera by reducing dark current noise that accumulates during extended exposure times. A plot of the standard deviation for dark noise as a function of exposure time can be seen in Figure 4.15.



Figure 4.15: Plot of standard deviation of mean dark noise signal against exposure time

4.6 Stray- light Analysis

The stray-light correction algorithm used for this thesis was described extensively in chapter three. Stray- light is modelled as a superposition of brightness which is a function of image data. The aim of this analysis was to test the stray- light algorithm on real scene images and also to investigate the effect of vignetting.

GretagMacbeth colour checker chart was used for this analysis. First, a reference measurement was made by capturing an image of the chart using a black background. The next step involved capturing an image of the chart using a white background. This introduces artificially generated stray - light into the image. Figure 4.16 shows GretagMacbeth colour checker chart image .



Figure 4.16: GretagMacbeth colour checker chart image used for stray- light analysis

Images captured using the white background were then corrected for stray - light as described in chapter three. Figures 4.17 and 4.18 show results for two patches, the reference measurement using the black background, and the same measurement after being corrected using the stray - light algorithm effect.

In Figure 4.17, the patch is located at the centre of the image. It can be seen that there is no considerable difference between the corrected frame and the reference frame.On the other hand, in Figure 4.18, the patch is positioned at the bottom left corner of the image sensor array. The results are poor compared to those were the patch was positioned at the centre of the image. The correction algorithm seems to have compensated more than was required. These errors can be attributed to vignetting at the edges of the image.



Figure 4.17: Plot of stray - light analysis on blue patch from GretagMacbeth colour checker chart image. The cross symbol represents the corrected signal while solid lines gives the orignal signa



Figure 4.18: Plot of stray - light analysis on red patch from GretagMacbeth colour checker chart image. The cross symbol represents the corrected signal while solid lines gives the orignal signal

4.7 Hyperspectral image registration

The aim of this section was to register hyperspectral images with sub-pixel accuracy. Two global registration algorithms were used for aligning hyperspectral images during this project. One algorithm used cross correlation as image similarity measure while the other used normalised mutual information . Both methods are presented and registration results are also given.

4.7.1 Experimental procedure

Checker board images were captured with a metal halide lamp placed on the left - hand side of the board (Figure 4.19). Image acquisition was repeated six times. A camera

aperture setting of 5.6 was used for this acquisition. The checker board was approximately 85 cm for the hyperspectral imaging system. Dark noise and flat field images were also captured using the same exposure time as those for scene acquisition. Radiance data was also captured using a telespectroradiometer positioned 3.20 m to the scene image centre. Checker board images were corrected using dark noise and flat field images.



Figure 4.19: Checker board image used for hyperspectral image registration analysis

Translation and scaling affine transforms were applied to images during the registration process. The translation affine transform was used for registering over replications of the same wavelength image while homothety (a combination of translation and scale) was used for registering over different wavelength images. The scaling factor is excluded from registering over replications of the same image since chromatic differences will be identical. The translation transformation matrix and scaling transformation matrix are

	1	0	δ_x		s_x	0	0	
given as Translation =	0	1	δ_y	, $Scale =$	0	s_y	0	
	0	0	1		0	0	1	

where δ_x , δ_y , s_x and s_y are transformation parameters to be estimated.

4.7.2 Cross correlation method

This method compensates for limited global chromatic difference by shifting local wavelengthindexed images to produce maximum overlap with a middle-wavelength reference image. Cross correlation was used as the image similarity measure. The Matlab optimizer *fminsearch* was used to obtain optimum shifts in scale and translation of the unregistered image for maximum overlap with the reference image. The unregistered image is finally adjusted using the optimal registration parameters.

4.7.3 Mutual Information method

This method can also perform translation and homothety registration. Normalised mutual information is used as an error measure. It measures the registration error between the unregistered and reference image. The quasi newton Matlab optimizer *fminlbfgs* is used to provide optimum shifts needed to achieve the optimal registration between both images with minimal registration error. Finally, the optimal registration parameters are used to transform the unregistered image.

4.7.4 Registration evaluation

Images were registered using both algorithms presented in sections 4.7.2 and 4.7.3. The six replications were registered over position using a translation affine transform with the third image used as the reference image.

Two approaches were used to register the averaged images. One approach registered images over wavelength using an homothety affine transform with the middle wavelength image (560 nm) used as the reference image. The other approach divided the wavelength range of the images into three parts and registered the central wavelengths of all three regions against the middle wavelength image (560 nm). The new central wavelength images were then used as references images to register their regions.

The metric used for determining the goodness of registration was tracking edge locations in the registered image. The idea behind this method is with unregistered images, due to chromatic differences, the midpoint of a particular edge location will be unstable for images of all wavelengths. After aligning the hyperspectral images, the midpoint of edge locations should be stable. Edge tracking was carried out to obtain edge spread functions and edge location midpoints. The algorithm used detects sharp edge profiles in the images, computes their edge spread function and, midpoint of the edge spread function which represents the midpoint of the edge to sub-pixel accuracy. The line spread function and its standard deviation were also computed.

Fourteen edge regions were selected from across the checker board image to test registration accuracy (Figure 4.20). Their edge midpoint locations and standard deviations were computed for both methods discussed. Plots of edge midpoint locations against wavelength for edge regions registered using cross correlation (central wavelength and three part approaches) and mutual information(central wavelength and three part approaches) can be seen in Figures 4.21,4.22,4.23 and 4.24 respectively. The difference between the maxmum and minimum edge midpoint location across wavlengths is given in Table 4.3.

From these results, it can be seen that both registration methods produced registration to sub-pixel accuracy but results were better using mutual information producing registration



Figure 4.20: Checker board image used for hyperspectral image registration analysis with 14 edge regions indicated on it using red rectangles



Figure 4.21: Plots of edge midpoint locations against wavelength for image registration using cross correlation and central wavelength image as reference image

error as small as 0.1 pixels. The largest registration error was found in edges at the boundary of the image. This can be explained as only the centre of the image was in focus during acquisition. The edge regions at the boundary of the image are not as sharp as those produced from the centre of the image.

The two approaches (three part optimisation and central wavelength registration) produced different results. Registration using the central wavelength as the reference image gave lower registration errors. For the rest of this thesis, images were registered using mutual information and the central wavelength as the reference image.



Figure 4.22: Plots of edge midpoint locations against wavelength for image registration using cross correlation and three part optimisation



Figure 4.23: Plots of edge midpoint locations against wavelength for image registration using mutual information and central wavelength image as reference image

4.8 Defective pixels

In most CCD detector array, a small percentage of pixels are defective in some way. These are pixels that do not respond to light at all, or respond in a nonlinear way. Such pixels may have extreme dark current as well. It is important to identify these bad pixels on the



Figure 4.24: Plots of edge midpoint locations against wavelength for image registration using mutual information and three part optimisation

Table 4.2: Difference between maximum and minimum edge midpoint location across wavelengths for edge images registered using Cross Correlation (CC) and Mutual Information (MI) and methods 1(Three part optimisation) and 2 (Central wavelength registration)

	CC Method 1	CC Method 2	MI Method 1	MI Method 2
Edge 1	2.38	1.64	0.6	0.56
Edge 2	0.72	0.44	0.22	0.32
Edge 3	2.46	1.74	0.72	0.68
Edge 4	0.6	0.5	0.18	0.16
Edge 5	0.36	0.34	0.38	0.2
Edge 6	1.18	0.9	0.54	0.36
Edge 7	0.96	0.86	0.7	0.32
Edge 8	0.42	0.38	0.4	0.18
Edge 9	0.88	0.66	0.2	0.2
Edge 10	0.9	0.62	0.14	0.1
Edge 11	0.32	0.28	0.26	0.08
Edge 12	0.52	0.42	0.44	0.26
Edge 13	0.64	0.42	0.52	0.2
Edge 14	0.82	0.64	0.44	0.28

chip and mask their values. Defective pixels can be grouped into three types namely hot pixels, dead pixels and stuck pixels.

4.8.1 Hot pixels

Hot pixels are individual sensors on the CCD chip with higher than normal output voltages. The rates of charge leakage for these pixels are extremely high. They can appear as small pixel sized bright points of light on longer exposures. Every pixel on the CCD has some charge leakage, and if exposed long enough, any pixel would light up. Hot pixels are dependent on the tempearture and gain of the CCD sensor. The warmer the CCD, the brighter the hot pixels will be. Typically with hot pixels, the dark current is 10 times higher than the average dark current³²

4.8.2 Dead pixels

These are pixels of the CCD sensor that do not react to light hence they have a low output and/ or poor responsitivity³². These pixels remain unlit no matter the amount of light hitting the CCD sensor array.

4.8.3 Stuck pixels

These pixels always outputs a high voltage at all exposures. It could be considered as a hot pixel that is permanently lit. Figure 4.25 shows an image where a stuck pixel is highlighted. It has a value higher than all other pixels considering either 4 or 8 pixel connectivity. Hot, stuck or dead pixels can be eliminated by estimating the pixel value



Figure 4.25: Image with a stuck pixel highlighted

from neighbouring pixels. This could be done by the averaging or obtaining the median of optional number of pixels around the defective one.

4.9 Main meridian analysis

One of the objectives of this chapter was to investigate the resolution of images produced by the hyperspectral imaging system in the main meridian (horizontal and vertical) at different locations in the field of view of the camera. This was accomplished by obtaining sample edge patches from the centre and near-boundary from the checker board hyperspectral image. Edge and line spread functions were constructed for this near-horizontal and near-vertical hyperspectral edge patches using the algorithm discussed in chapter three. The standard deviation from each fit was computed and recorded. A plot of the standard deviation against wavelength for each sample edge is presented in Figure 4.26.



Figure 4.26: Plot of LSF standard deviation for near- horizontal and near - vertical hyperspectral edge patches

Results show no significant difference between the standard deviations for horizontal and vertical edge images sampled from the centre of the image with an average standard deviation of 1.3 pixels. This result is similar with those obtained in previous work using the same hyperspectral imaging system²⁴. On the other hand, the standard deviation for edges obtained from the centre and near boundaries had a significant difference. Results depend on the focus setting of the camera and vignetting at the boundaries.

4.10 Calibration Verification

The final test image analysis involved verifying system calibration, image correction and compensation algorithms reported so far. The overall performance of the system was assessed by acquiring and processing images from a GretagMacbeth colour checker chart and then comparing the derived reflectances with those obtained with a telespectroradiometer. Reference Munsell chips N7,N5 and N2.5 were inserted at the edges of the chart (Figure 4.16). Flat field and dark noise images were also acquired. This process involved capturing six consecutive images under identical conditions, registering over position and subsequent averaging to get an image which is ideally free of temporal noise.
Immediately after acquisition, the spectrum of light reflected from each patch and Munsell chips was recorded by PR650 telespectroradiometer. The averaged GretagMacbeth colour checker chart image was then corrected for dark noise and spatial non-uniformity using an averaged dark noise image and flat-field image. The image was further corrected for stray- light effects and registered over wavelength using the central wavelength image as the reference image. Spectral reflectance functions for each pixel of the corrected image was then computed by normalizing this corrected signal at each pixel against that obtained with the reference munsell chips inserted in the scene.

A plot showing the ratio of mean signal for yellow - green and orange patches is given in Figure 4.27 while the ratio of purple and orange patches is given in Figure 4.28. Symbols show data for the hyperspectral system and continuous lines for the telespectroradiometer.



Figure 4.27: Spectral reflectance data for ratio between yellow-green and orange patches of GretagMacbeth colour checker Chart

The root mean square error in the hyperspectral estimates of reflectance across the set of test surfaces was 0.0025. Although some small systematic distortions were present in some regions of the spectrum, the overall accuracy of the hyperspectral system was sufficient for further analysis in later chapters.



Figure 4.28: Spectral reflectance data for ratio between purple and orange patches of GretagMacbeth colour checker Chart

CHAPTER FIVE

APPLICATION 1: IMAGING ARCHIVED MATERIALS

5.1 Introduction

The previous chapter outlined calibrations that were done on the hyperspectral imaging system and the hyperspectral image registration algorithms used for this thesis. In this chapter, applications of these methods are discussed. The registration of hyperspectral images acquired from the University of Manchester's John Rylands Library is given. The experimental procedure and metrics used to test the accuracy of the algorithm are also considered.

5.2 Hyperspectral image registration

The aim of this work was to produce high resolution hyperspectral images that will help in identifying accurate matches for colours used in document restoration at the university of Manchester John Rylands Library. Presently, staff use their eyes as cues for determining the colour used to restore or repair old books or paintings. Hyperspectral images will give distinct spectral data for each pigment hence making the matching task easier and accurate.

5.2.1 Experimental Procedure

Images were captured in a room with a metal halide lamps providing illumination. Each scene capture was repeated four times. Two focus settings were used. For the first focus setting, the image at 560 nm was sharp while for the second setting, image at 720 nm was sharp. The scene was 75 cm from the hyperspectral imaging system. The camera's aperture setting was 5.6. Dark noise and flat field images were also captured. Radiance data were captured using a telespectroradiometer positioned 3 m to the scene image centre. Scene images were corrected using dark and flat field images.

5.2.2 Image registration and averaging

Images were registered using the mutual information algorithm presented in chapter four. The four replications were registered over position with the second image used as the reference image. The algorithm was modified for this registration. The scaling factor was excluded since for replications, chromatic differences are identical. After registering over replications, their average was obtained and this averaged image was then registered over wavelength with the image captured at 560 nm used as the reference image. The final registered images were then stored and ready for analysis. Figure 5.1 and 5.2 show the averaged registered image of two scenes called hagaddah and woodcut respectively.



Figure 5.1: Hagaddah Image



Figure 5.2: Woodcut Image

5.2.3 Evaluation of image registration accuracy

It is necessary to estimate how accurate the registration actually is. The method used in this project involves tracking edge locations in the registered images. The idea behind this method is with unregistered images, due to effect of chromatic differences, the midpoint of a particular edge location will be unstable in all 33 images. After aligning the hyper-spectral images, the midpoints of the edge locations should be stable. The software used detects sharp slightly slant edges in the image, computes its edge spread function(ESF) and, midpoint of the edge spread function(which represents the edge to sub-pixel accuracy). The line spread function(LSF) and its standard deviation are also computed. These parameters are computed for unregistered and registered images. Plots of edge midpoints and the standard deviation of the line spread function against wavelength can be seen in Figure 5.3 and 5.4.



Figure 5.3: Plot of standard deviation and edge midpoint location of hagaddah image

From figure 5.3, the curve for the plot of standard deviation for the edge spread function of the haggadah image surprisingly was flat for both focus settings. While the plot for the woodcut image gave the expected result since for one setting, it was out of focus for the reference image (560 nm). Further acquisition of other documents and paintings needs to be done as these results are inclusive.



Figure 5.4: Plot of standard deviation and edge midpoint location of woodcut image

CHAPTER SIX

APPLICATION 2: SCENE RECOGNITION

6.1 Introduction

Scene recognition is an active research area. One of the problems which affects imaging scene recognition algorithms is the variability of objects appearance as illumination and scene geometry changes. Slight changes in the viewing conditions causes a large variation in the scenes appearance.

In this chapter, two methods are used to achieve scene recognition. One method uses spectral gradients which are descriptors invariant to scene geometry and illumination. The other method uses ratio indexing for scene recognition. A novel approach to obtaining image ratios is proposed.

6.2 Spectral gradient

Spectral gradient algorithm used in this thesis was proposed by Angelopoulou et al³. The algorithm works by cancelling variations in scene geometry and incident illumination. This is done by examining the rate of change of reflected intensity with respect to wavelength. The assumption used is one where the incident illumination remains stable over small intervals in the visible spectrum. They acquired grey scale images using different colour filters and computed the spectral derivatives of the scene. The collection of spectral derivatives computed at different wavelength forms a spectral gradient. This is a surface reflectance descriptor, invariant to scene geometry and incident illumination for smooth diffuse surfaces.

When light from a scene falls on a photosensitive sensor, the amount of light reflected I from each point p(x, y, z) in the scene depends on the light illumination of the scene E and the surface reflectance S of the material:

$$I(p,\lambda) = E(p,\lambda)S(p,\lambda)$$
(6.2.1)

where λ represents the wavelength and depends on the incident and reflected light on the wavelength. The reflectance function $S(p, \lambda)$ depends on the surface material, the scene geometry and the viewing and incidence angles⁶⁹.

When the spectral distribution of the incident light does not vary with the direction of light, the geometric and spectral components can be separated:

$$E(\theta_i, \varphi_i, \lambda) = e(\lambda)E(\theta_i, \varphi_i) \tag{6.2.2}$$

where (θ_i, φ_i) are the spherical coordinates of the length light direction vector and $e(\lambda)$ the illumination spectrum. The scene brightness is then represented by Equation 6.2.3

$$I(p,\lambda) = e(p,\lambda)E(p,\theta_i,\varphi_i)S(p,\lambda)$$
(6.2.3)

When the logarithm of the image irradiance equation is taken, the multiplicative effect is changed into an additive one:

$$L(p,\lambda) = \ln e(p,\lambda) + \ln E(p,\theta_i,\varphi_i) + \ln S(p,\lambda)$$
(6.2.4)

The next step is computing the partial derivative of the logarithmic image with respect to wavelength since the aim is investigating how the natural logarithm of an image varies over wavelengths in the visible spectrum.

$$L_{\lambda} = \frac{e_{\lambda}(p,\lambda)}{e(p,\lambda)} + \frac{S_{\lambda}(p,\lambda)}{S(p,\lambda)}$$
(6.2.5)

where $e_{\lambda}(p, \lambda) = \partial e(p, \lambda) / \partial \lambda$ is the partial derivative of the spectrum of the incident light with respect to wavelength and $S_{\lambda}(p, \lambda) = \partial S(p, \lambda) / \partial \lambda$ is the partial derivative of the surface reflectance with respect to wavelength.

Illumination although not constant, is assumed to change slowly over small increments of wavelength. This means that its derivative with respect to wavelength is approximately zero. ($e_{\lambda}(p, \lambda) \approx 0$). This assumption fits well with our hyperspectral imaging system as images are acquired at 10nm intervals. It is safe to assume that the partial derivatives of logarithmic images depends on the surface reflectance.

$$L(p,\lambda) = \frac{S_{\lambda}(p,\lambda)}{S(p,\lambda)}$$
(6.2.6)

6.2.1 Experimental procedure

The aim of this section was to determine whether two regions (in the same or different scenes) are represented by objects with similar or distinct reflectance functions and whether these objects can be identified. In order to compute the spectral derivatives images were capture under two illumination conditions. Two metal halide lamps and a tungsten lamp were used. The first condition combined a metal halide and a tungsten lamp, while the other used two metal halide lamps. In each setup, both lamps were angled 45 degrees to the centre of the imaged objects. The imaged objects were positioned 100 cm from the hyperspectral imaging system. The camera's aperture setting and focus setting were 5.6 and 1.3 respectively. The usual procedure was followed. Images of the scene were captured first, then a flat field image and dark image were also captured. Radiance data for inserted calibration standards was also captured using a PR-650 telespectroradiometer. Scene images were then corrected using the dark noise images and flat file images and converted to radiance data using data from the calibration standards and telespectroradiometer. The corrected images (Figure 6.1) were then stored for analysis.



Figure 6.1: GretagMacbeth colour checker chart image used for spectral gradient analysis

6.2.2 Spectral gradient computation

For each corrected image, its logarithmic image was generated. In the logarithmic images, the value stored at each pixel was the natural logarithm of the original image intensity. Figures 6.2 and 6.3 show an original image and its logarithmic equivalent captured at 570 nm . As seen from this figure, the logarithmic image preserves the overall appearance of the original image. However the maximum intensity values were scaled down significantly. From a maximum value of 4096 in a 12-bit image to a maximum value of 3.61.

The next step was computing the spectral derivatives of the logarithmic images. Differentiation was done using finite differencing. The spectral gradients were computed over the wavelength interval 10nm by subtracting subsequent logarithmic images in the sequence producing a total of 32 spectral gradients images. The spectral gradient at each pixel is a



Figure 6.2: Image captured at 570 nm with a scale bar showing pixel intensity



Figure 6.3: Logarithmic image of image acquired at 570 nm with a scale bar showing pixel intensity

vector consisting of 32 spectral gradients. This vector was expected to remain constant for materials with the same reflectance function, independent of illumination changes. Figure 6.4 shows the correlation coefficients between the two imaging conditions used for all 24 patches of the GretagMacbeth colour checker chart .

From these results, it can be seen that spectral gradients are unique and are not affected by illumination change but when the colours are almost the same shade like with the grey patches, the method breaks down.



Figure 6.4: Spectral gradient plot for two lighting conditions

6.3 Scene Recognition

Object recognition methods are predominantly based on geometric image properties that, in principle, are invariant under changes in viewpoint. By contrast, approaches to recognition based on colorimetric properties depend little on viewpoint. One such method colour indexing was developed by Swain and Ballard⁵⁹, who used colour histograms and histogram intersection to determine matches between test and reference images obtained under different viewing conditions. The colour axes used for the histograms were opponent and non-opponent combinations of the red, green, and blue components of the triplets (r, g, b) at each point. The method was generally robust to variations in viewpoint and scene background, but had limited invariance to changes in illumination, as the red, green, and blue components were simply normalized by their sum.

Funt and Finalyson²⁵ improved the illumination invariance of colour indexing by replacing the red, green, and blue components of the triplet (r, g, b) at a point by the corresponding triplet of spatial ratios defined across adjacent points; that is,(r1/r2, g1/g2, b1/b2) for points 1 and 2 (they actually used a Laplacian or first directional derivatives of the logarithm of the colours). Such spatial ratios are relatively stable under changes in illumination, although not exactly invariant. Funt and Finalyson²⁵ noted that if the sensor spectral sensitivities were broad, as with the cone photoreceptors of the eye, then indexing performance was worse, but by transforming spectral sensitivities so that they were spectrally narrower or sharper, almost perfect indexing performance could be obtained with their test and reference images. These were Mondrian-like, abstract coloured patterns under different illuminations. Somewhat lower performance was obtained with images of real objects²⁵.

Whether spectral sensitivities are broad or narrow, however, there is a more general problem with using three sensor spectral sensitivities, in that according to some behavioural measures^{41,45}, reliable surface identification by spectral sampling requires more than three degrees of freedom, in particular with natural scenes of the kind illustrated in Figure 6.5.



Figure 6.5: Eight of the 50 natural scenes used in this work²⁴

In principle, increasing the number of sensor classes over the available wavelength range should increase the reliability of the colour signal by reducing the number of false matches, and therefore produce better recognition performance. On the other hand, more sensor classes might reduce the number of correct matches and increase the level of noise.

One of the objectives of this work was to extend scene recognition using ratio indexing to hyperspectral images and compare results with RGB images. The other was to determine how many sensor channels are needed for the reliable recognition of scenes under different illuminations when test and reference images are sparsely and independently sampled. Sparse independent sampling was used to capture the spatial uncertainties that, under other imaging conditions, could arise by occlusion or change in viewpoint.

Simulated Mondrian patterns were used for analysis of the first objective. While the analysis of the second objective was based on 50 natural scenes, represented as hyperspectral images. Each scene was simulated under daylight illuminants with different correlated colour temperatures (CCTs). Unlike the procedure used by Funt and Finalyson²⁵, where spatial ratios were drawn from neighbouring points in the scene, spatial ratios were here obtained by taking signals from pairs of points chosen at random across the scene.

6.4 Ratio Indexing

Ratio indexing identifies an object by comparing its ratios to the ratios of each object in a database. Funt and Finlayson computed their ratios from neighbouring RGB pixels. For this work, ratios were computed from random pairs since more spectral information is available with the thin slices provided by hyperspectral imaging. Ratios of sensor signals were obtained as follows, at each scene point i = 1, 2, ..., N of the sample, let $q_i = (q_i^1, q_i^2, ..., n)$ be the n - tuplet of sensor responses in classes 1, 2, n, and let $(q_1, q_2, , q_N)$ be the N - vector of these *n*-tuplets. Let σ be a random permutation of the points 1, 2, N. Then the set of sample ratios consists of the (unordered) set of N values $q_1/q_{\sigma(1)}, q_2/q_{\sigma(2)}, q_N/q_{\sigma(N)}$, where each of the quotients $q_1/q_{\sigma(1)}$ is given by $q_i^1/q_{\sigma(i^1)}, q_i^2/q_{\sigma(i^2)}, ..., q_i^n/q_{\sigma(i^n)}$.

Ratio histograms were formed from these sets of ratios, but with unequal bin sizes to accommodate the non-uniform distribution of ratios from a uniform distribution of colours, as in^{25} .

6.5 Histogram Intersection

The intersection of a test image histogram H_a with a reference image histogram H_b is given in Equation 6.5.1 as

$$I(H_a, H_b) = \frac{\sum_{j} \min(H_a(j), H_b(j))}{\min(\sum_{j} H_a(j), \sum_{j} H_b(j))}$$
(6.5.1)

where j indexes the bins used to form the histograms. Necessarily, $0 \le (H_a, H_b) \le 1$.

6.6 Image database

The next two sections presents the database used for scene recognition. One was made up of 100 simulated Mondrian pattern hyperspectral images while the other contained 50 natural scene images.

6.6.1 Mondrian patterns

One of the objectives of this work was to extend scene recognition using ratio indexing to hyperspectral images. A controlled randomized test set of 100 synthetic hyperspectral images of Mondrian patterns were generated from approximately 1200 reflectance Munsell spectra. Ten of these simulated mandarin patterns can be seen in Figure 6.6.

Mondrian pattern spectra were simulated with CIE correlated colour temperature (CCT) 4000 K and 25000 K. Each hyperspectral image had spatial dimensions 1344 x 1024 pixels and spectral range 400 nm - 720 nm sampled at 10 - nm intervals. Ratios of spectral



Figure 6.6: Ten of the 100 simulated Mondrian pattern images used for scene recognition

radiances were created by taking pairs of points at random as described earlier. The number of wavelength channels used for recognition was 7 rather than all 33 due to limits on computer calculations with ratio histograms of more than seven dimensions. The 7 wavelength channels used were those for 420 nm, 470 nm, 520 nm, 570 nm, 620 nm, 670 nm, 720 nm.

For comparison, hyperspectral images were also simulated using a luminance band and three RGB bands. RGB images were generated using Nikon camera, human cone sensitivities. RGB images from human cone sensitivities were further transformed using a method known as spectral sharpening²⁵.

6.6.2 Natural scenes

A database of 50 natural scenes was used for scene recognition and thumbnail illustrations of eight of those images can be seen in Figure 6.5. Some of the larger set are available in³⁹. Details of how the hyperspectral data were obtained and of their accuracy are given in²⁴ and are similar to those described in this work. Each hyperspectral image had spatial dimensions 1344 ×1024 pixels and spectral range 400 nm - 720 nm sampled at 10 nm intervals, thereby providing a discrete representation of an effective spectral reflectance $R(\lambda; x, y)$ at each wavelength λ and position (x, y) in the scene. The effect of illuminating the scene by a particular illuminant with spectrum $E(\lambda)$ was simulated by multiplying $R(\lambda; x, y)$ at each point (x, y) by $E(\lambda)$. The assumptions and approximations involved in this approach have been discussed in²⁴, Appendix A. Because of the approximately 1.3pixel line spread function of the camera system used to acquire the hyperspectral data²⁴, only non-adjacent pixels were spatially sampled. Daylight spectra were simulated from those described by the CIE¹¹ with CCTs of 4000 K, 6500 K, and 25000 K, characteristic of the sun and sky at different times of the day.

A sensor system with a variable number n of sensor channels was simulated by taking the average bandwidth of a commercial RGB sensor (a Nikon D1 digital camera¹⁴), and then replicating a triangular spectral sensitivity with this bandwidth at evenly spaced points over the visible spectrum, as illustrated in Figure 6.7 for three examples, with seven, five, and two sensor channels. The maximum number of sensor channels possible in the present simulation was limited to seven due to computational cost. No attempt was made in this

analysis to optimize the spectral locations of the sensors according the characteristics of the scene being sampled.



Figure 6.7: Examples of spectral sensitivities of simulated variable-channel system with 7, 5, and 2 sensor channels, and of the spectral sensitivities of a Nikon D1 camera, the CIE photopic luminance function, and the spectral sensitivities of the cone fundamentals.

For comparison, the sensors of a Nikon D1 camera, the CIE photopic luminance function¹¹, and the spectral sensitivities of the cone photoreceptors, i.e. the cone fundamentals¹¹, were also used.

Spatially random samples of size N = 10, 100, 1000 and 10000 points were taken from images of scenes under a daylight of CCT 4000 K or 25000 K to act as test sets and from images of scenes under a daylight of CCT 6500 K to act as the reference set. Critically, the spatial samples in the test and reference sets were drawn independently. Scene recognition was also done for all the spatial points in the image.

6.7 Results

The results of scene recognition are divided into two parts. Results for recognition using the simulated Mondrian hyperpsectral images is given first. As this was a preliminary application, the metric used to determine recognition accuracy was the mean false alarm rates computed from histogram intersection. The second part presents results for scene recognition for natural scenes. A discrimination index was used for evaluating recognition accuracy and is explained in a later section.

6.7.1 Mondrian patterns

Matching values from histogram intersection were computed for members of the image database, from which hit and false-alarm rates from signal detection provided summaries of recognition performance. Hit rates were uniformly 100, but mean false-alarm rates varied markedly with the number of bands: approx. 74% with the luminance band, 37% with human cone RGB bands, 29% with Nikon camera RGB bands, 23% with Sharpened human cone RGB bands and just 17% with seven hyperspectral bands (Figure 6.8). From these results it can be seen that ratio indexing based on more than three wavelength bands may offer significant advantages in object recognition.



Figure 6.8: Plot of mean false alarm rate against sensor classes for simulated Mondrian pattern ratio histograms

6.7.2 Natural scenes

With 50 scenes, there are 50 possible correct matches, i.e. the test and reference samples come from images of the same scene, and $50 \times 49 = 2450$ false matches, where the test and reference samples come from images of different scenes. Let HR be the match hit rate

defined by the mean of I(Ha, Hb) over the 50 correct matches and let FAR be the match false-alarm rate defined by the mean of $I(H_a, H_b)$ over the 2450 false matches. Both HR and FAR were expected to vary with the number of sensor channels. Thus, as the number of sensor channels increases, the conditions for a match become more demanding, and so the hit rate should decrease but so also should the false-alarm rate.

The true level of recognition depends on the difference between the two, although this needs to be expressed on a scale that takes into account the limitations of the measure, i.e. intersection, which as a proportion varies between 0 and 1. One common approach is to summarize the difference between HR and FAR by the discrimination index d' from signal-detection theory; that is, $d' = \Phi^{-1}(\text{HR}) - \Phi^{-1}(\text{FAR})$, where Φ is the normal cumulative distribution function. This index has the advantage of both linearising proportions and reducing the effects of bias.

Figures 6.9 and 6.10 show discrimination index d' plotted against the number of sensor classes of each type for 10, 100, 1000 and 1000 points drawn randomly from the images. They also include discrimination index d' plotted aginst number of sensor classes for the whole image (1376256 points). The two plots are for test images obtained under a daylight of CCT 4000 K and under a daylight of CCT 25000 K matched against reference images obtained under a daylight of CCT 6500 K.



Figure 6.9: Plot of discrimination index d' against number of sensor classes for images simulated with CCT 4000 K matched against images simulated with CCT 6500 K

The interpretation of differences in d' values with different numbers of sensor classes is complicated by the constraints imposed by the number of scenes being sampled (the more scenes there are, the greater FAR even though HR remains constant). Importantly, however, the dependence of mean d' on the number of sensor channels in the variable-



Figure 6.10: Plot of discrimination index d' against number of sensor classes for images simulated with CCT 25000 K matched against images simulated with CCT 6500 K

channel system appears to peak with five sensor channels, after which it levels off and possibly declines with six and seven sensor channels.

CHAPTER SEVEN

SUMMARY AND FURTHER WORK

There were two main aims in this thesis. The first was to identify the main sources of error in a common design of focal - plane hyperspectral imaging system and devise ways of compensating for these errors. The second was to achieve scene recognition using hyperspectral images. The first aim was considered in chapter four while the second in chapter six. Images used in this thesis for the scene recognition task were images of natural scenes and simulated Mondrian patterns. Imaging of archived materials from the University of Manchester's John Rylands Library was also addressed in this thesis. In this chapter, Main results from this thesis will be considered. Further work will also be recommended.

7.1 Main results

7.1.1 Calibration

Input- output function was computed to investigate the linearity of the imaging system by recording data using a neutral density wedge, diffuser and quartz halogen bench lamp. Results showed that the hyperspectral imaging system was linear even at the shorter wave-lengths which suffers from low illumination. The nominal wavelength accuracy of the Liquid crystal filter used in the imaging system was investigated by capturing images of a mercury vapour lamp with the underlying idea that mercury vapour lamps have principal lines in the visible spectrum⁶⁹. The principal lines investigated were at 436 nm and 546 nm. Results showed a maximum variation of 0.6 nm for line at 436 nm and a variation of 0.9 nm for the line at 546 nm. These results are less than 1 nm and were deemed accurate for further work in this thesis. Two global image registration algorithms were tested on hyperpsectral data. The first one used cross correlation while the second used mutual information. The metric used for determining the goodness of registration was tracking edge locations in images. Results showed mutual information method gave better registration results compared to its cross correlation counterpart. The overall performance of the system was assessed by acquiring and processing images from a GretagMacbeth

colour checker chart and then comparing the derived reflectance with those obtained with a telespectroradiometer. The root mean square error in the hyperspectral estimates of reflectance across the set of test surfaces was 0.0025 and was seen as sufficient for further work.

7.1.2 Scene recognition

Scene recognition was done using spectral gradient computation and ratio indexing. For spectral gradient computation, spectral derivatives of the scene image were computed and the collection of spectral derivatives computed at different wavelength forms a spectral gradient. Spectral gradient is a surface reflectance descriptor, invariant to scene geometry and incident illumination for smooth diffuse surfaces. Images of a GretagMacbeth colour checker chart were acquired for two imaging conditions. Their spectral gradients were computed and a correlation coefficient was used to compare images from both imaging conditions. Results showed that spectral gradients are unique and are not affected by illumination change but when the colours are almost the same shade like for the grey patches in the chart, the method breaks down.

Scene recognition using ratio indexing was done on natural scene images and simulated Mondrian pattern images. The process involved obtaining ratio pairs from images, forming histograms from these ratios and then compare using histogram intersection. Ratios were created from random pairs. Ten sensor classes were used ranging from CIE photopic luminance function to seven channels of hyperspectral data. Sparse independent sampling of points simulate occlusion and change in viewpoint. Results showed that with just one sensor channel of the simulated variable channel system, there was little difference in performance between it and the CIE photopic luminance function, both yielding chance levels of scene recognition. But as expected, as the number of channels in the variable-channel system increased, recognition performance increased. With three sensor channels, there was little difference between its performance and that of the Nikon sensors and of the cone fundamentals. As the number of channels in the variable-channel system increased beyond three, performance continued to increase but reached a maximum with about five channels. The failure to increase further may be due to several factors. One possibility alluded to earlier is a decreased signal-to-noise ratio with more channels; another possibility is the potential confound introduced by summarizing recognition performance by a single measure when both match hit rate and match false-alarm rate are varying. In any event, with small samples, it seems that indexing with five sensor channels has advantages over indexing with three sensor channels for the recognition of natural scenes.

7.2 Further work

7.2.1 Hyperpspectral Image registration

The image registration algorithm used for this thesis is global. The use of local image registration or a combination of both approaches may increase registration accuracy. Global registration methods could be used to register replications of the image as only a translation transform is applied. A local registration algorithm could then be used for registering over wavelength. Care needs to be taken on the window size to be used for local registration. If the window size is too small, the registration parameters become unstable and if it is too large, it becomes global registration. An investigation into these factors was not possible within the constraints of this thesis work.

7.2.2 Scene recognition

During the scene recognition task, no attempt was made to optimize the spectral locations of the sensors according the characteristics of the scene being sampled. A selection of optimal spectral locations of the sensors could increase scene recognition accuracy. The image database used for scene recognition contained 50 natural scenes. A larger database could test the robustness of the algorithm.

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